Study of Reliability, Availability and Maintainability (RAM) of Industry 4.0 in INDIAN Perspective

Thesis submitted

by

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Statement of Originality

I Saptarshi Das registered on September 11, 2019 do hereby declare that this thesis entitled "Study of Reliability, Availability and Maintainability (RAM) of Industry 4.0 in INDIAN Perspective" contains literature survey and original research work done by the undersigned candidate as part of Doctoral studies.

All information in this thesis have been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by these rules and conduct, I have fully cited and referred all materials and results that are not original to this work.

I also declare that I have checked this thesis as per the "Policy on Anti Plagiarism, Jadavpur University, 2019", and the level of similarity as checked by iThenticate software is 4%.

Saptarshi Das.

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Date: 10/09/2025

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CERTIFICATE FROM THE SUPERVISOR

This is to certify that the thesis entitled "Study of Reliability, Availability and Maintainability (RAM) of Industry 4.0 in INDIAN Perspective" submitted by Sri Saptarshi Das who got his name registered on September 11, 2019 for the award of Ph. D. (Engineering) degree of Jadavpur University is absolutely based upon his own work under the supervision of Prof. (Dr.) Bijan Sarkar, Professor, Department of Production Engineering and that neither his thesis nor any part of the thesis has been submitted for any degree/ diploma or any other academic award anywhere before.

Bijan Sarkar 10 September 2025

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Saptarshi Das

(SAPTARSHI DAS)

Dedicated to my respected

Sir and Madam

Prof. (Dr.) Bijan Sarkar and Mrs. Nila Sarkar

ABSTRACT

As India is the 4th largest economy in the world and aiming towards the top three spot, we have to focus on the Manufacturing and service sectors. The topic **"Study of Reliability, Availability, Maintainability (RAM) of Industry 4.0 in INDIAN perspective"** is associated with the digitalization of the Indian Industry, especially the Manufacturing and service sectors and their quality improvement. Industry 4.0 is referred to as the fourth industrial revolution, where the machinery is smart, i.e. different systems and subsystems of machines are connected through different sensors and actuators, and a seamless communication has been established among them for smooth operation. Such a system should be reliable enough for delivering better output as well as available for operation over a stipulated period. To operate such a system seamlessly, the management should have a vast knowledge of the different types of failures associated with the systems, modes and effects of failures, severities of failures, remaining life before the failures and adaptation of necessary maintenance strategies to overcome such failures. The prime goal of the research work is to provide a framework for better operation of a smart system and also to identify its probable faults and necessary maintenance tasks. Different works have already been carried out in this regard. Based on the limited scope, the research work has focused on three different domains. First one based on the theoretical architecture of a smart factory, where A layer-wise reliability and Availability analysis has been carried out using expert elicitation. The second study has considered a SMART Arsenic Iron removal plant (AIRP), where a Rough set-based Reference Ideal Method (R-RIM) has been implemented on the system for its Failure assessment. Based on the holistic failure assessment, the criticality of the failure Modes has been identified, and respective ranks have been assigned to them. Lastly, the sensitivity analysis has been conducted to analyse the effects of the criteria on the failure mode. The last case study has been taken from an Aluminium smelting plant, where a detailed study has been conducted on an IoT-based weight data communication system (WDCS), and based on its architectural overview, the potential faults have been identified, and a fault tree diagram has been constructed in this regard. Considering the uncertain environment, the Fuzzy fault tree (FFTA) analysis has been conducted for the reliability assessment of the system, and Reliability-centred Maintenance (RCM) has been implemented on the system for its reliability improvement. Secondly, the FFTA has been upgraded by incorporating the Fermatean-Fuzzy Set (FFS), and the combined approach has been applied for further reliability assessment, where superior results have been achieved. Based on the obtained results, a Bayesian Network (BN) has been constructed for fault diagnosis of the system and identification of the most critical subsystem. Based on the outcome, the Autoregressive Integrated Moving Average (ARIMA)

time series model has been implemented to predict the Remaining Useful Life (RUL) of the critical subsystem. In this study, only the RUL predicting equation has been developed.

Considering all the past and present research works, the prime aim has been set to implement the appropriate maintenance strategies as well as to improve the life of a system associated with Industry 4.0. Along with that, the reliability and availability assessment and their application in the maintenance policy have been structured in a single frame. The work has been carried out considering the Indian perspective for the well-being of the Indian society.

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Chapter 1

Introduction

1.1 Brief overview of Industry 4.0

Change is the rule of nature; nothing is permanent here, and whatever has come will go. This epic philosophy of the **Shrimad Bhagwat Geeta** has also been observed in the global industrial revolution. The journey of the modern Industrial Revolution started with the invention of the steam engine. Nowadays, it continues its journey in the form of Industry 4.0 with the aid of advanced technologies like the Internet of Things (IoT), Artificial Intelligence (AI) and Data analytics. Industry 4.0 connects the physical assets with digital technologies through different sensors and probes and allows for better collaboration and access among departments, partners, vendors, products, and people. Industry 4.0 is driven by a need to boost efficiency as well as effectiveness to become more agile to respond to market unpredictability, improve quality, and enable new business models. This concept is gaining more attention due to its ability to automate the manufacturing process as well as its real-time monitoring and harnessing big data for analytics-driven decision-making. The key technologies associated with Industry 4.0 have been demonstrated in terms of pillars, as shown below.

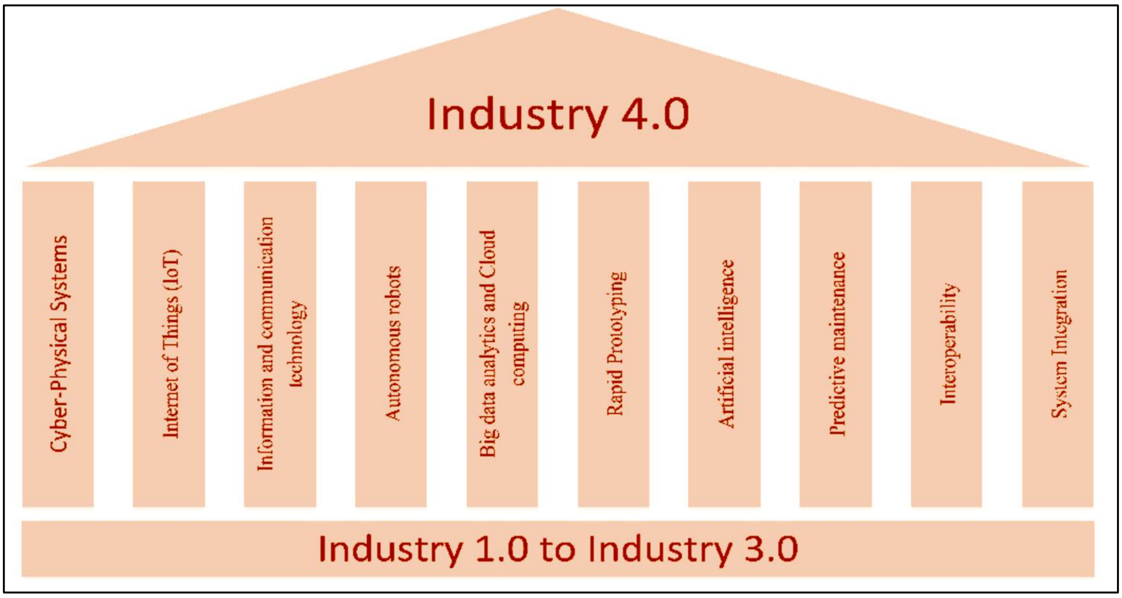

Fig 1.1 Pillars of Industry 4.0 (**Source:** Digalwar et al. 2023)

The key aspects of Industry 4.0 and the role of information and communication technologies (ICT) have been discussed briefly.

i) Digital Transformation

Industry 4.0 is fundamentally about the digital transformation of manufacturing, involving the integration of digital technologies to improve processes, enhance efficiency, and create intelligent systems.

ii) Connectivity and Data

ICT enables the creation of interconnected systems where machines, control systems, and software can communicate and share data. This is crucial for real-time monitoring, analytics, and predictive maintenance.

iii) Intelligent Factories

Industry 4.0 aims to create intelligent factories that can respond dynamically to changing needs and conditions, using data analytics, AI, and automation.

iv) Enhanced Productivity and Flexibility

By automating tasks, optimizing processes, and enabling real-time decision-making, Industry 4.0 aims to increase productivity and flexibility in manufacturing.

1.2 India and Industry 4.0

The Indian government, too, is aware of the need to implement Industry 4.0 and has already taken steps in this direction. A significant improvement in the Global Network Readiness Index has been observed over the past eight years, with the ranking shifting from 91st place in 2015 to 49th in 2024. Robot density in manufacturing industries increased substantially from 3 (Per 10000 employees) in 2016 to 7 (Per 10000 employees) in 2021, though it remains far behind the global average of 141. The digital economy is a key driver of economic growth, contributing approximately 11% to the country's GDP in 2023, with the potential to reach 20% by 2026. An adequate as well as significant research trend has been observed after the COVID-19 period, where digitalization is a key factor for the Indian economy. A holistic overview of Industry 4.0 from the Indian viewpoint has been provided by Bhat (2022). The Indian economic structure, along with a detailed analysis of the industrial workforce, has been studied by Mehta et al. (2019), and they have concluded the study by focusing on the upliftment of skills among the Indian workforce for the adaptation of new technologies. Pasi et al. (2020) have studied the sustainability of Industry 4.0 technologies under Indian manufacturing sectors and found that smart sensors and robot arms have a high sustainability in manufacturing sectors, and on the other hand cyber cyber-physical systems (CPSs) and big data analytics have low sustainability, and they have also encouraged skill upliftment. The preparedness of Industry 4.0 in the Indian environment has been empirically analysed by Singhal (2021). In the study, it has been found that during the paradigm shift of the industries, the necessity of adequate skills is essential for the successful implementation of Industry 4.0 across the value chain. The necessary skills have also been identified, e.g. Analytics, Data management, data security, Human–machine interface, Data science, etc. However, the major challenges in adopting Industry 4.0 technologies in India (Confederation of Indian Industry, 2024) include:

- Lack of Awareness
- Technological Barriers
- Financial Constraints
- Lack of Skilled Workforce

To counter such challenges, RAM (Reliability, Availability, Maintainability) analysis is a perfect choice for such industries from a sustainability point of view. It acts as a powerful engineering tool in order to identify the critical components and bottlenecks of the manufacturing process, as well as the maintenance action optimization. A brief discussion of RAM analysis is given below.

1.3 Reliability, Availability, Maintainability (RAM)

Reliability, availability, and maintainability (RAM) analysis are important methods for reducing maintenance costs and enhancing system function and operation. Reliability (R) is the probability that a system will operate over a specified period under given conditions. Maintainability (M) involves analyzing downtime, which includes periods when a system or component is unavailable due to inspection, testing, or preventive and corrective maintenance activities. Lastly, availability (A) refers to the probability that the system will be in an operational state at a future time. RAM analysis is essential for increasing productivity, efficiency, and product quality. Additionally, the RAM methodology guides us toward continuous improvement based on total quality management (TQM) principles. The core goals of this analysis are to improve system availability and reliability by using two key parameters: mean time between failures (MTBF) and mean time to repair (MTTR). There is a key relation among Availability, MTBF, and MTTR (Shrinath, 1991) has been given in terms of a formula.

$$Availibility\ (A) = \frac{MTBF}{MTBF+MTTR} \tag{1.1}$$

Where R is directly associated with MTBF, and M is associated with the MTTR. Hence, a pictorial representation among the three parameters, i.e. Availability (A), Reliability (R), and Maintainability (M), has been chalked out and shown below.

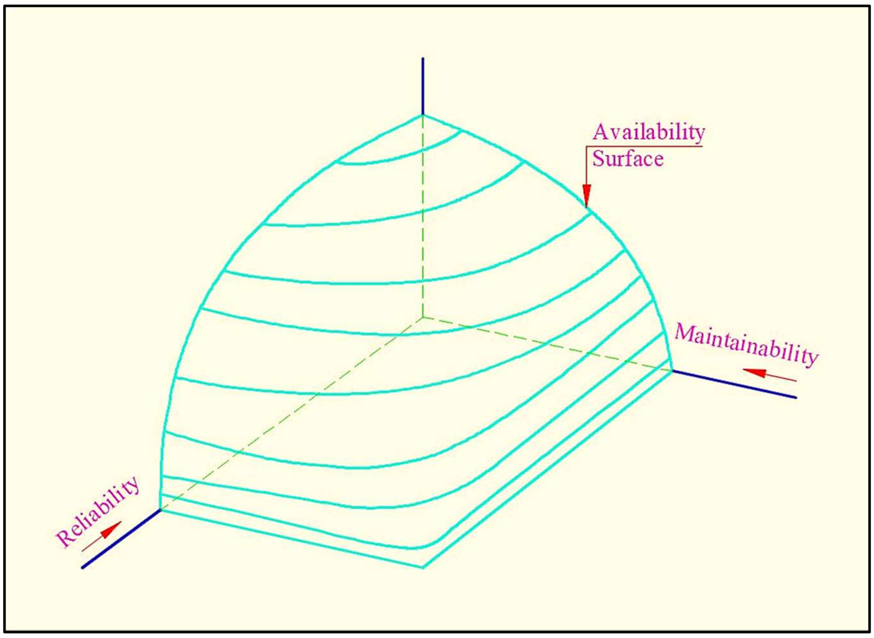

Fig.1.2 A holistic view of Reliability, Availability and Maintainability (RAM)

The RAM has a vast application in different domains, such as Automotive manufacturing (Soltanali et al. 2019), Conveyor systems in mechanised tunnelling (Ahmadi et al. 2019), Ice Cream Industry (Tsarouhas, 2020), Plug-In Electric Vehicle (Talukdar et al. 2021), etc. In this study, such methodology has been utilized in the Industry 4.0 domain for health assessment as well as to identify the risks associated with the domain. This study has shown the reliability and availability assessment of a typical Industry 4.0 domain under an uncertain environment, followed by risk assessment, Maintenance strategy, and remaining life estimation of the allied domain under a similar environment, and the work has been carried out from an Indian perspective.

Chapter 2

Bibliometric literature review of the Research work

2.1 Introduction

Before proceeding to the chapter, two key terms of the title have been identified, namely 'Bibliometric' and 'Literature Review'. Firstly, we have to identify that the meaning of Bibliometrics is the statistical analysis of the scientific and academic literature, through which one can identify the propensity, pattern, gravity, and intellectual structure of the domain. On the other side, the literature review of a research work is defined as a methodical, structured, as well as explicit method for rumination, exploration and elicitation of adequate knowledge from related existing works practised by the researchers, scholars and other allied persons. Hence, the Bibliometric literature review of a respective research work aimed to reveal the inner knowledge, trends, statistics and impact of the research domain by churning the existing research works. To carry out the Bibliometric literature review of the present work, 4 (Four) domains have been identified that are the tributaries of the entire research work. The entire literature review is based on the information received from the Scopus database. The detailed Bibliometric literature review of those domains has been discussed below.

2.2 Study on Reliability, Availability, and Maintainability Assessment of Industry 4.0

The Bibliometric literature review of the said study has been carried out over a period of 25 years (2000-2025). The search has been based on Reliability, Availability, Maintainability, and Industry 4.0, where a total 2630 number of published documents have been found. While uncertainty analysis has been incorporated into the remaining search, the number has been decreased to 827. On the other hand, when the uncertainty analysis was replaced by India by keeping the rest options as same, the result was found as only 482. The temporal trends, country-wise trends, and Author-wise trends of the publication have been observed during the review. Those trends have been discussed in brief with analytical charts.

2.2.1 Temporal trends in publication

To understand the trend, the last 20 years of data, i.e. from 2005 to 2025, have been considered. The trend has shown an impressive improvement in this research area, especially over the last 10 years. This is because of the global adoption of the Industry 4.0 concept. A significant increase in the said study was observed after 2020. This was because, after the COVID-19 pandemic, the manufacturing sector was shifting towards automation, and this trend continued. The temporal trend in the publication of the said study is shown in Fig. 2.1.

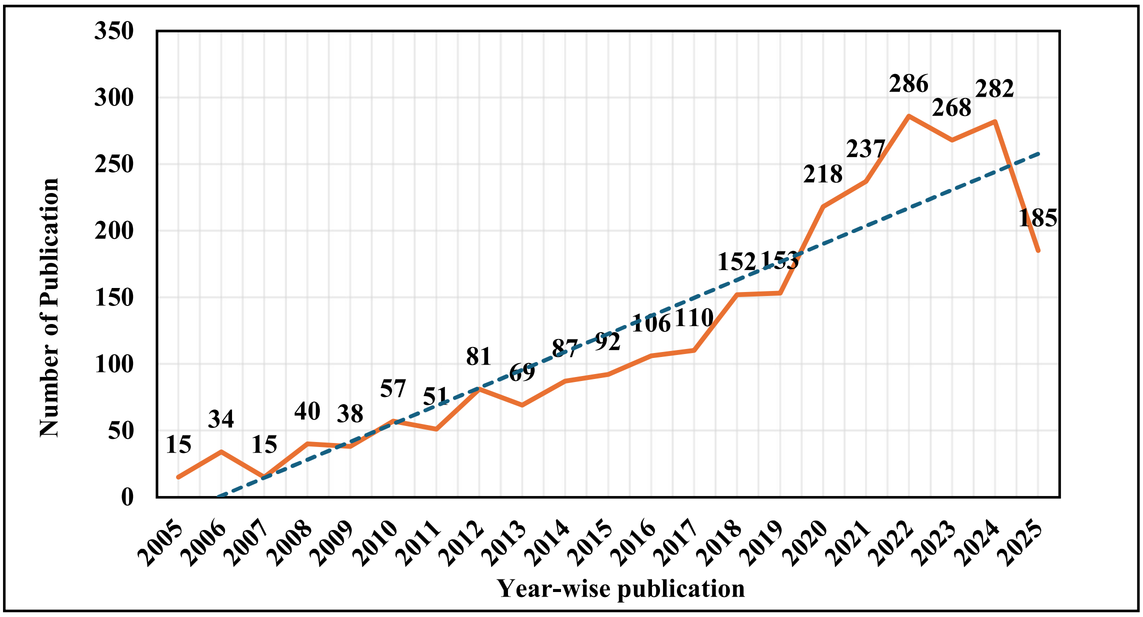

Fig. 2.1 Temporal trends in publication on the Study on Reliability, Availability, and Maintainability Assessment of Industry 4.0

2.2.2 Country-wise trends in publication

The country-wise trends show the United States in the leading spot with 361 publications, followed by India in the second spot with 324 publications. The improvement of India in this domain is quite impressive, and this is due to certain initiatives taken by the Government of India, such as the Make in India programme, PM Gati Shakti National Master Plan, Industrial Corridor Development Programme, National Logistics Policy, etc. The country-wise trend of publication of the following study is shown in Fig. 2.2. The leading ten countries with their numbers of publications have been reflected in the figure.

2.2.3 Author-wise trends in publication

The author-wise trend regarding this research work has been displayed in Fig. 2.3. Based on the review, the top 10 authors who have contributed to the related research field have been included along with their number of publications on the said domains. It has been observed that the authors have made a vast contribution to the Fuzzy set theory, MCDM, Reliability assessment and allied fields.

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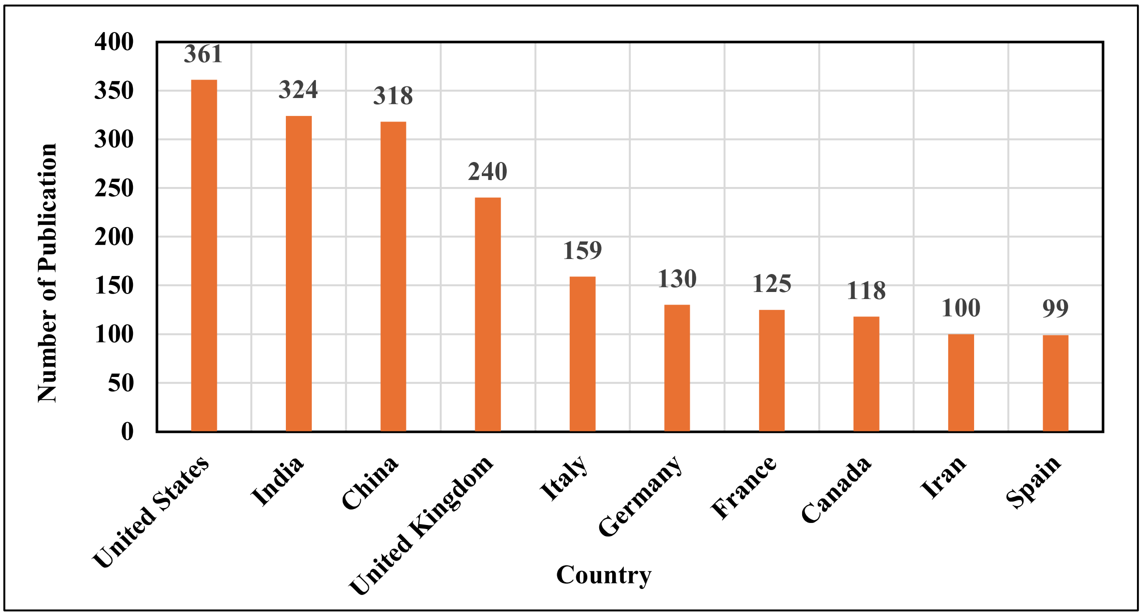

Fig. 2.2 Country-wise trends in publication on the Study on Reliability, Availability, and Maintainability Assessment of Industry 4.0

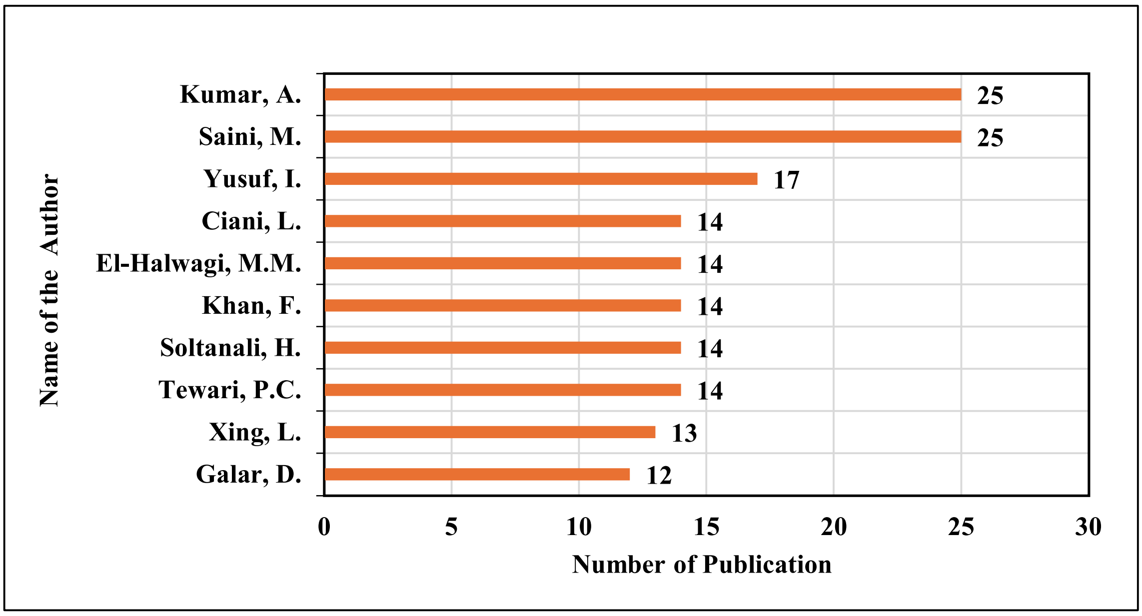

Fig. 2.3 Author-wise trends in publication on the Study on Reliability, Availability, and Maintainability Assessment of Industry 4.0

2.3 Study on risk assessment of an Industry 4.0 domain under an uncertain environment

Under this section, the focus of the study has been shifted towards the risk assessment of a typical smart system, which falls under the Industry 4.0 architecture. This study has been conducted under an uncertain environment. Hence, during the literature survey, the search options were restricted to Industry 4.0, multicriteria decision making (MCDM), risk assessment, and uncertainty analysis. Based on the unification of all search options, a total of

7753 documents have been found in the Scopus database. As this research work has been conducted in an Indian environment, this is why the term "Indian context" has also been included with the remaining options, and consolidating all the search options, a total of 1192 documents have been found. But a holistic approach has been taken during the literature survey, and the overall number of documents, i.e. 7753, has been considered for assessment of Temporal trends, Country-wise trends, and Author-wise trends of the said study.

2.3.1 Temporal trends in publication

The temporal trends of the study have shown a significant uplift in the research activity since 2014. This is because of the rapid implementation of smart systems in different industries, and enforcing them to identify the potential risks associated with the systems. The temporal trends in the publication of the study have been shown in Fig. 2.4.

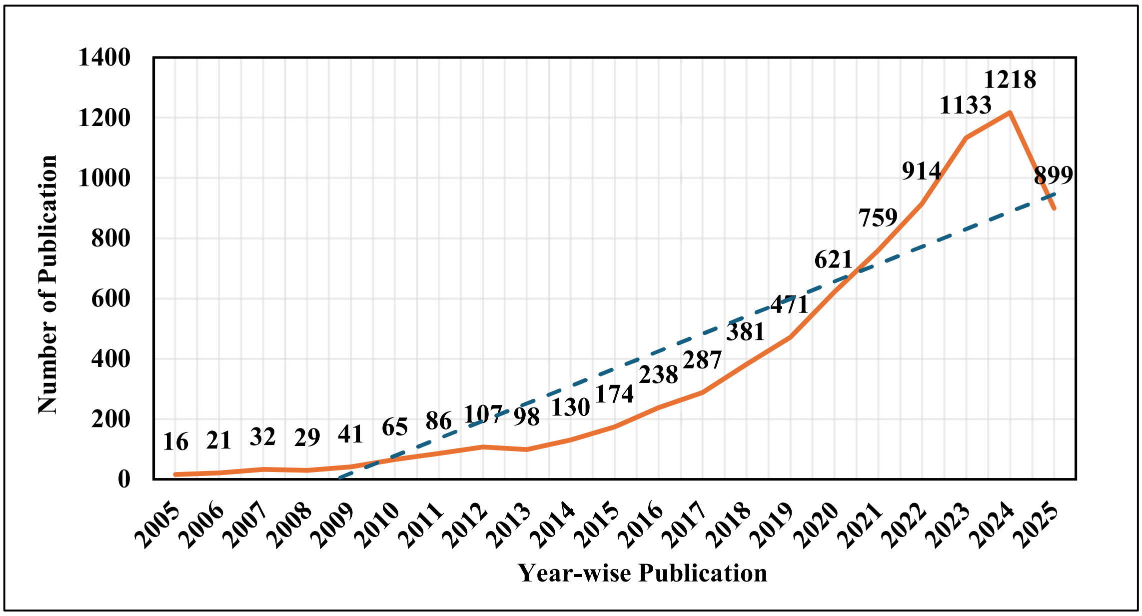

Fig. 2.4 Temporal trends in publications on the Study of risk assessment of an Industry 4.0 domain under an uncertain environment

2.3.2 Country-wise trends in publication

The Country-wise trends in the publication of the study for the top 10 countries are shown in Fig. 2.5. China is at the top of the leaderboard as it is the "MANUFACTURING HUB" of the world. On the other hand, India is in the second spot, but there is a large gap regarding publications in the respective fields. Due to recent industrialisation, a growing trend has been observed. Apart from that, some leading manufacturing industries are now adopting the Industry 4.0 concept.

2.3.3 Author-wise trends in publication

The top 10 authors and their respective contributions to the said study have been displayed in Fig. 2.6. The top 3 authors have a significant contribution to Fuzzy decision making, MCDM Decision support systems, etc.

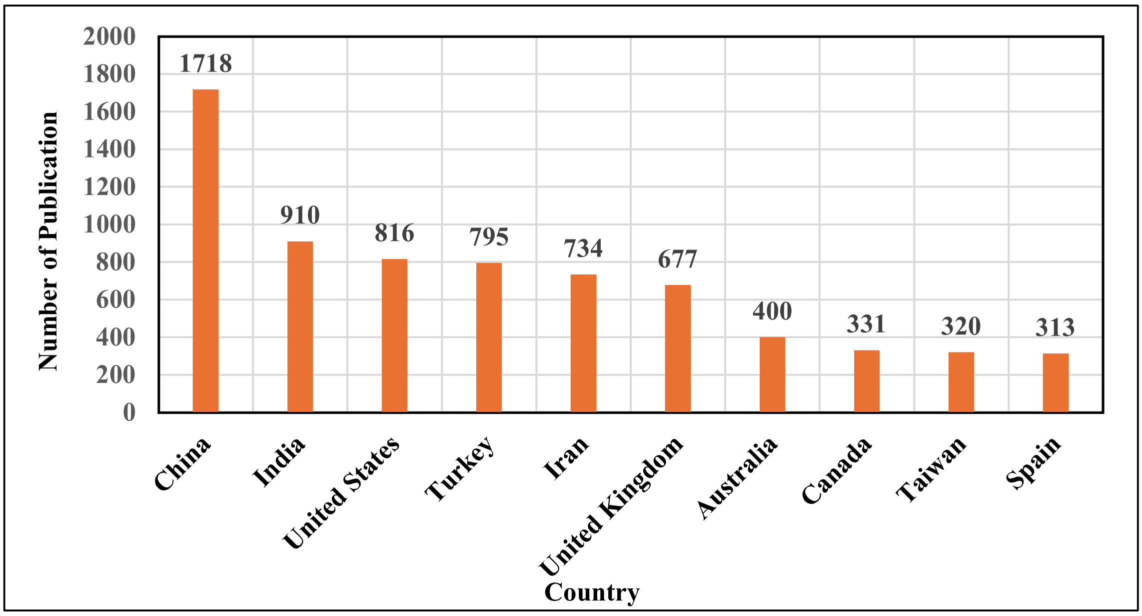

Fig. 2.5 Country-wise trends in publication on the Study of risk assessment of an Industry 4.0 domain under an uncertain environment

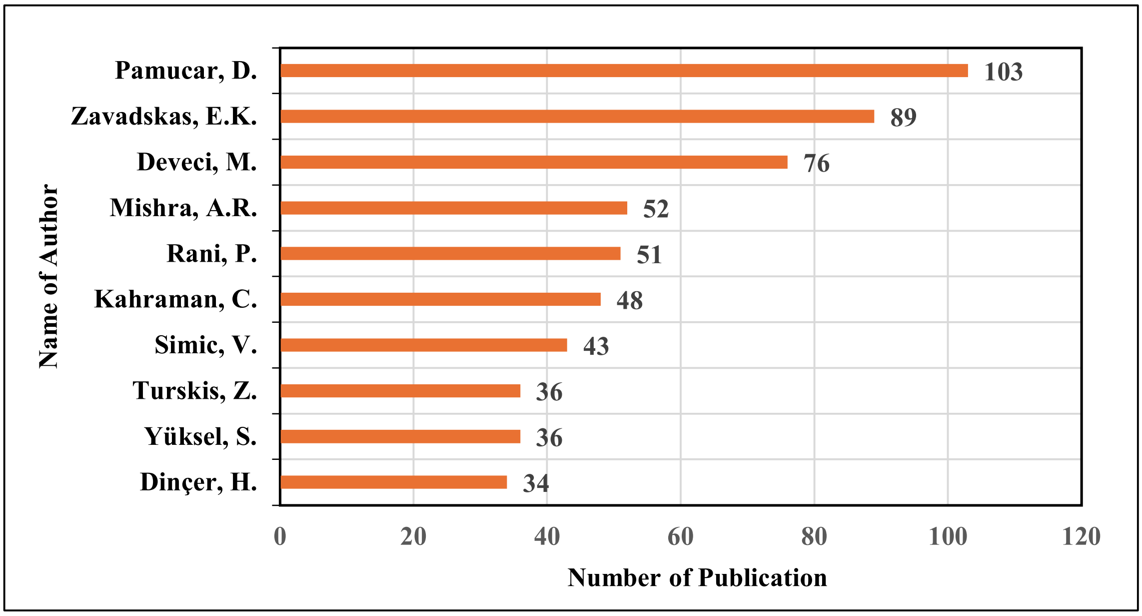

Fig. 2.6 Author-wise trends in publication on the Study of risk assessment of an Industry 4.0 domain under an uncertain environment

2.4 Study on Reliability-Centred Maintenance (RCM) of Industry 4.0 environment using system failure assessment

This section has provided the ideas of different failures associated with the different systems of Industry 4.0, and the implementation of the maintenance strategies based on their reliability. Firstly, the literature survey has been conducted based on three options, namely, Reliability Centered Maintenance (RCM), Fault analysis and Industry 4.0 through the Scopus database and a total number of 1584 documents have been displayed by the database. When uncertainty analysis is added to the option, keeping others as unaltered, the result decreases to 650. The addition of the uncertainty analysis is due to the unavailability of raw failure data. Alike the previous studies, the Temporal trends, Country-wise trends, and Author-wise trends have been discussed below.

2.4.1 Temporal trends in publication

A moderate slope has been observed in the temporal trend of the study. But a significant increase in publications can be observed from 2019 onwards. This trend signifies the study as an emerging field. The Temporal trends in publication on the Study are shown in Fig. 2.7.

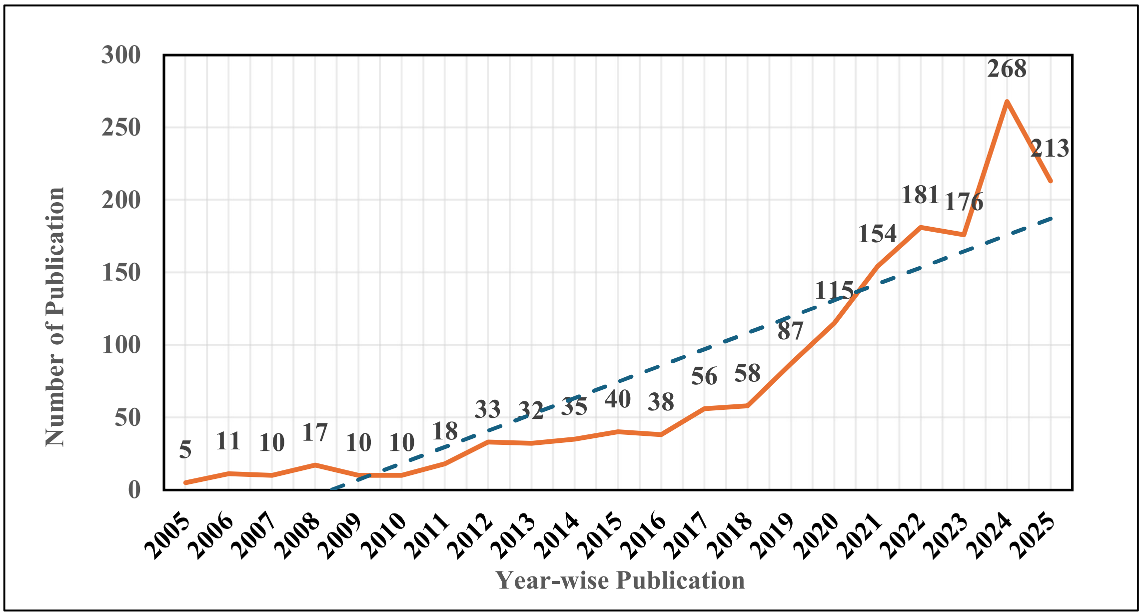

Fig. 2.7 Temporal trends in publication on the Study of Reliability-Centred Maintenance (RCM) of Industry 4.0 environment using system failure assessment

2.4.2 Country-wise trends in publication

The country-wise trend has shown China's dominance in this field. The condition of India is much weaker compared to the other countries. The focus has to be given to the uncertainty analysis as well as different decision support systems operated under a vague environment. The Country-wise trends in publications are presented in Fig. 2.8.

2.4.3 Author-wise trends in publication

The author-wise trend of the study has been portrayed in Fig. 2.9. The leading authors have already published various articles in the fields of Maintenance management, Reliability, Industrial engineering, and allied fields.

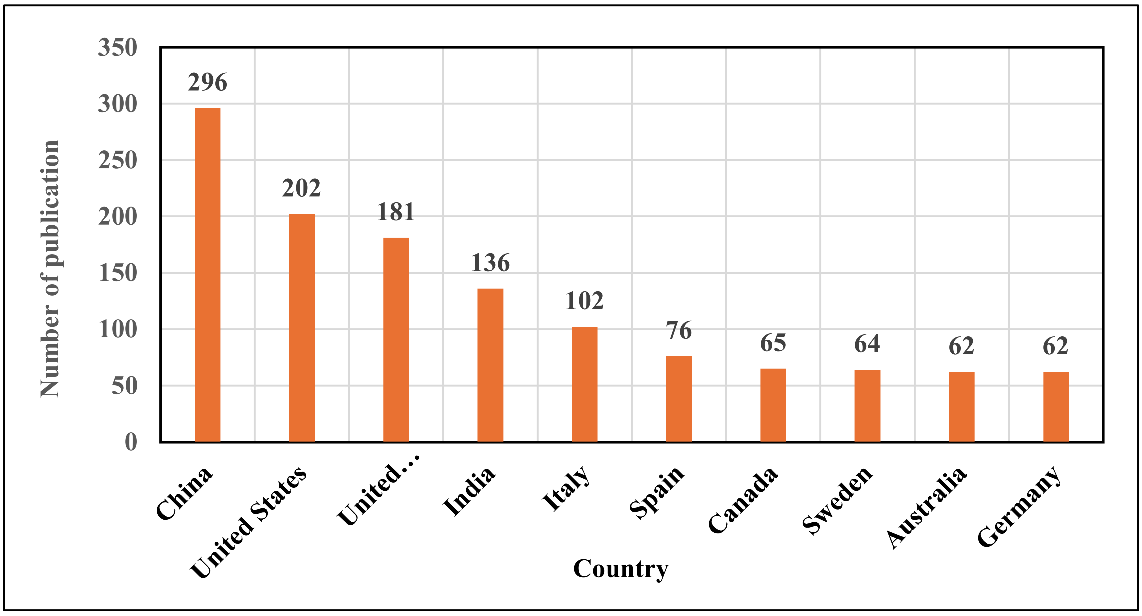

Fig. 2.8 Country-wise trends in publication on the Study of Reliability-Centred Maintenance (RCM) of Industry 4.0 environment using system failure assessment

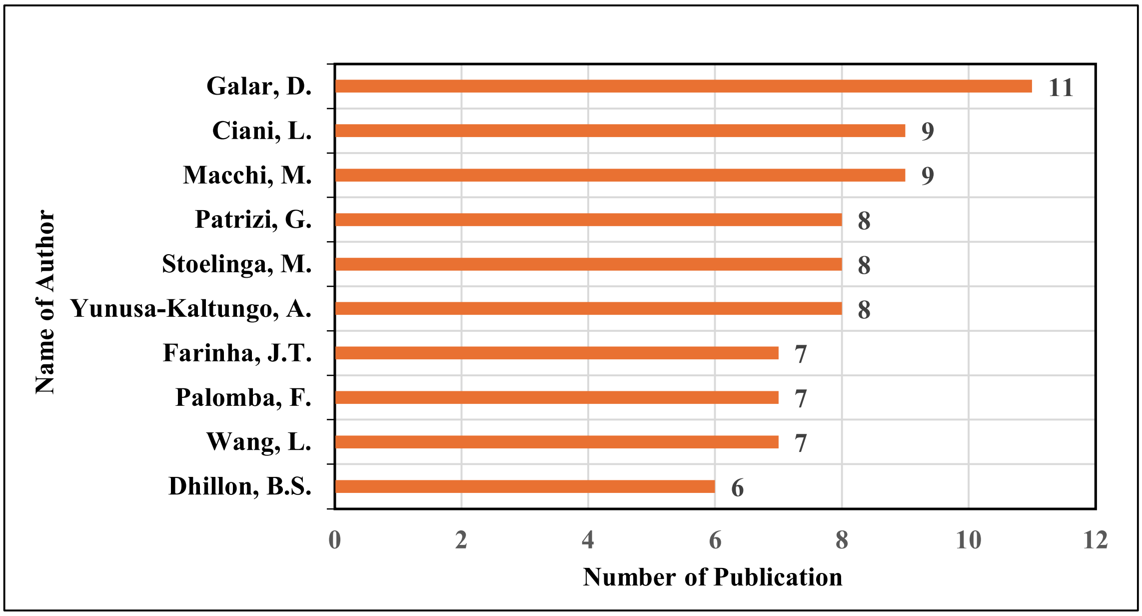

Fig. 2.9 Author-wise trends in publication on the Study of Reliability-Centred Maintenance (RCM) of Industry 4.0 environment using system failure assessment

2.5 Study of fault Diagnosis and prognosis of an Industry 4.0 architecture under an uncertain environment

This study is associated with the current and remaining life of the system under an uncertain environment, i.e. this study signifies the health condition of the system. The Scopus database represents a total of 1743 documents over the period of 25 years (2000-2025). The option has been given as: Industry 4.0, fault Diagnosis, Prognosis, uncertainty analysis during document search.

2.5.1 Temporal trends in publication

The sharp uplift of the trendline determines the current research interest in this study. Due to the propagation of Industry 4.0 all over the world, industries are more concerned about the health of the systems as well as their remaining life. This assessment will help them to adopt precise maintenance strategies to avoid any unwanted breakdown.

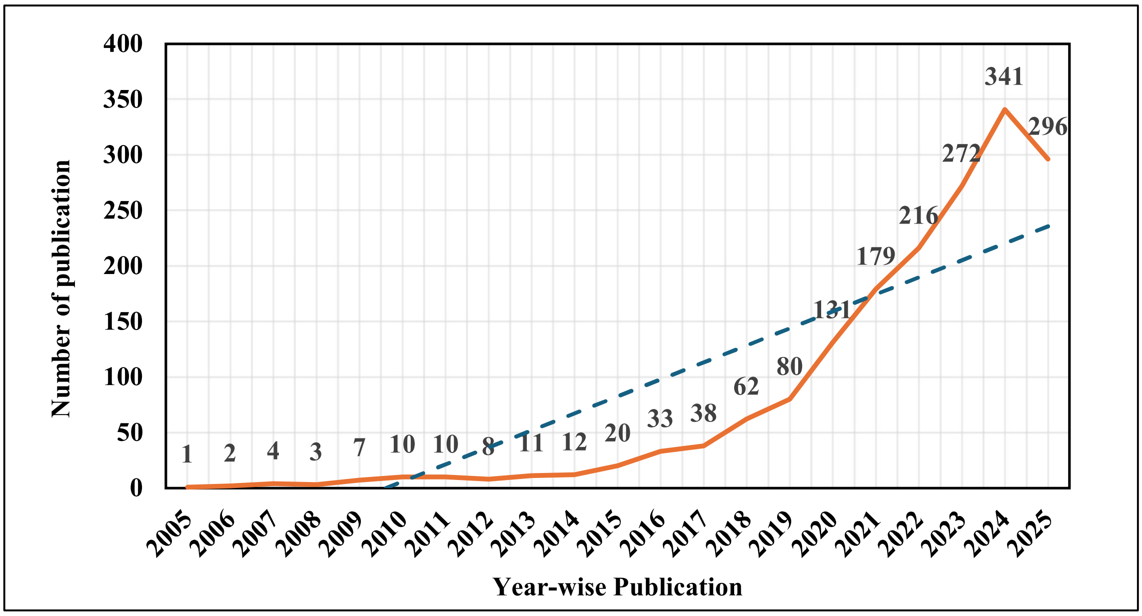

Fig. 2.10 Temporal trends in publication on the Study of fault Diagnosis and prognosis of an Industry 4.0 architecture under an uncertain environment

2.5.2 Country-wise trends in publication

The country-wise trends, as shown in Fig. 2.11, indicate significant drawbacks from the Indian viewpoint. Compared to China and other leading countries, India is far behind, with only 111 research documents. To overcome the situation, the leading industries associated with the Industry 4.0 environment should have to focus on this matter and encourage research on the respective study.

2.5.3 Author-wise trends in publication

The Author-wise trends in publication are shown in Fig. 2.12. The leading authors have engaged in the fields of Safety, Risk, Smart Manufacturing, Mechatronics and other allied fields.

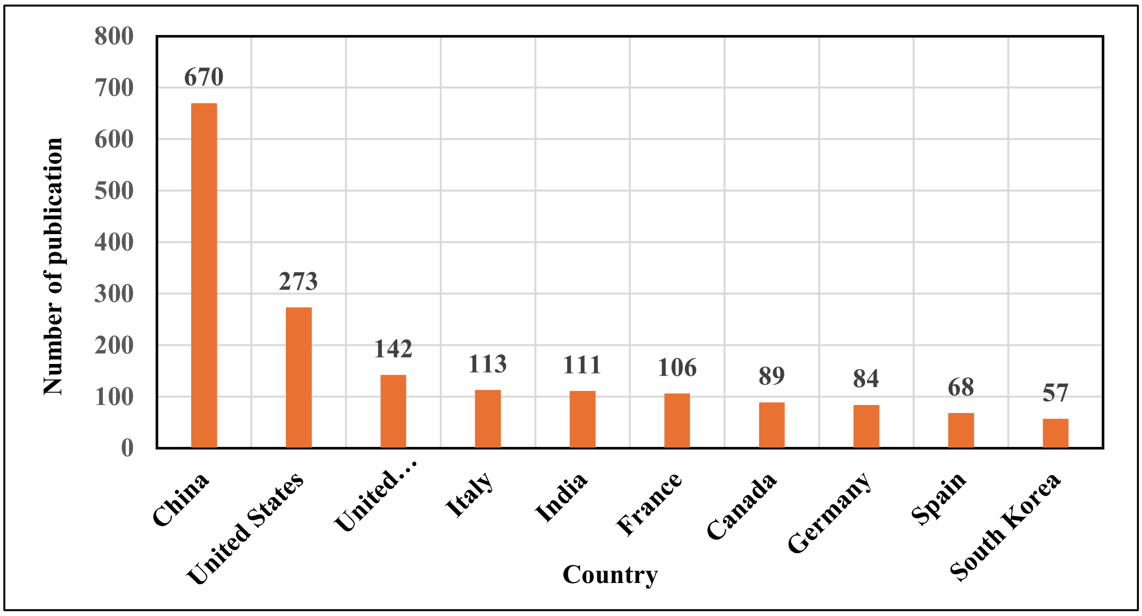

Fig. 2.11 Country-wise trends in publication on the Study of fault Diagnosis and prognosis of an Industry 4.0 architecture under an uncertain environment

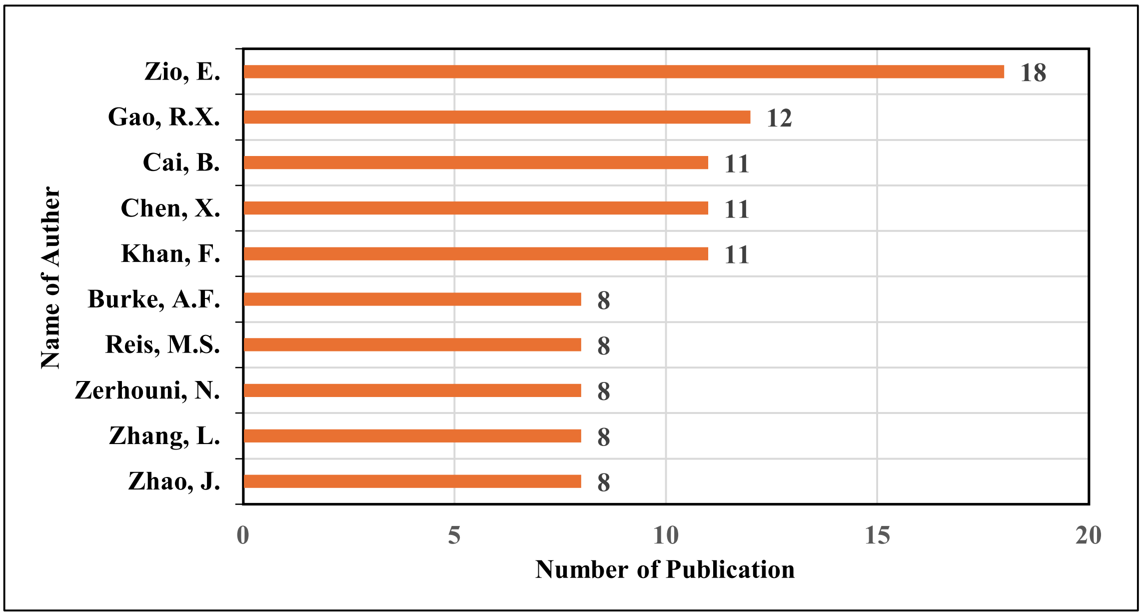

Fig. 2.12 Author-wise trends in publication on the Study of fault Diagnosis and prognosis of an Industry 4.0 architecture under an uncertain environment

Chapter 3

Systematic literature review of the study

3.1 Reliability & Availability Assessment of Industry 4.0 under an uncertain Environment

3.1.1 Smart factory

The concept of the smart factory system has been provided by Shi et. al. (2020). The study has an emphasis on the basics, challenges and new technology associated with the smart factory. A systematic literature review on smart factory has been constructed by Osterrieder et. al. (2020). This study has identified eight sub-categorical subjects that are associated with the smart factory. A layer-wise explanation has been given by Chen et. al. (2017). A case study on a smart factory system has been given in the study. An outlook regarding the implementation of smart factory has been proposed by Wang et. al. (2016). Mabkhot et al. (2018) have revealed the requirements of a smart factory. A survey has been conducted in this regard. The potential risks of a smart factory have been discussed by Herrmann (2018). The automated inspection policy of the Smart factory has been discussed along with the necessary mathematical analysis by Sett et al. (2020). The security issues and challenges of a smart factory, along with their respective solutions, have been discussed by Yi et al. (2022).

3.1.2 Markov analysis

For the assessment of system reliability of a repairable system, the basic idea of the Markov model has been provided by Billinton, R. (1992). This method has been used in different domains for reliability evaluation as shown by Zhang et. al. (2021), along with an application of such a model on the heat exchanging system of deep-sea manned submersibles. The reliability analysis of a communication system has been discussed by Kumar et. al. (2020). The mathematical modelling of the Markov analysis has been discussed in detail. The Markov model has been used by Samanta et. al. (2001) for reliability assessment of a Heavy earth-moving machine used in a mine. Ge et al. (2010) evaluate the Reliability of equipment and substations using the Fuzzy-Markov process, where the probabilities with uncertainties have been represented by a fuzzy membership function. Binh et al. (2006) have drawn the Reliability curve of a power system using the parameters that have been assessed through Fuzzy Markov analysis. The concept of Single-Valued and Interval-Valued Neutrosophic Hidden Markov Model has been proposed by Nagarajan et al. (2022). An idea of the Entropy-Based modelling method has been given by Kong et al. (2019). Chung et al. (2000) have demonstrated the concept of Entropy-Based Markov Chains and elaborated its application in multisensor fusion. An example of an entropy-based Markov model has been provided by Zhao et. al. (2016), where the Hybrid multi-carrier energy system has been considered as a case study. Due to the unavailability of sufficient data, the expert's opinion has been considered for the research work. A combined approach of Adam Optimization and the Maximum Entropy Markov Model has been implemented by Tahir et al. (2020) for the development of a human activity recognition model.

3.1.3 Reliability and Availability assessment under a vague environment

An idea of Fuzzy Markov chain has been given by Avrachenkov, K. E. et. al. (2002). To decode the qualitative failure data, the concept of Fuzzy set theory has been adopted from the research work of Mohanta et. al. (2005). The preliminary concept of Fuzzy Mean Time to Failure (MTTF) and Fuzzy Mean Time to Repair (MTTR), along with their membership function, has been considered for the research work. The idea of fuzzy scale and membership function for fuzzy failure rate and repair rate has been provided by Tanrioven, M. et. al. (2004). Chandna et al. (2014) have discussed an engineering reliability model in a fuzzy environment. They have applied the fuzzy reliability evaluation approach to estimate the input failure rates of the system. The fuzzy analysis of availability characteristics of a machining system, that is comprising of multi-active units and multi-standby units, has been described by Shekhar et al. (2014). A fuzzy-based reliability model has been adopted by Chang et al. (2015) for the assessment of system reliability of a labour-intensive manufacturing system, considering its repair actions.

3.2 Risk assessment of a smart AIRP system

3.2.1 Failure Mode Effects Analysis (FMEA)

A detailed overview of the FMEA concept has been provided by Mikulak et al. (2017), where they have elaborately explained the concept of FMEA and its measuring procedure. In this study, the concept of RPN has been elaborately discussed. A brief overview of FMEA has been provided by Sharma et al. (2018), where the types of FMEA have been discussed. According to the overview, the area-wise application of FMEA has been shown. The critical component of a rake unloading system has been assessed by Sing et al. (2017) using Failure Mode Effects and Criticality Analysis (FMECA) along with Fault Tree Analysis (FTA). FMECA is an upgrade of FMEA. Similarly, the Reliability analysis of a starting and landing system of an unmanned aerial vehicle has been evaluated by Jiang et al. (2019). In this study, Fuzzy Risk Priority Number (FRPN) has been considered for counter multiple failure modes. The FMEA approach has also been applied in the healthcare system by Rezaei et al. (2018). The FMEA-based Root cause analysis (RCA) technique has been applied to reassess the RPN index. For countering the vagueness of the FMEA parameters, Balaraju et al. (2019) adopted a fuzzy-based FMEA approach for risk assessment of a Load-Haul-Dumper (LHD) Machine. They have adequately explained the Fuzzy-FMEA approach, and the result has been derived using MATLAB. A similar approach has been adopted by Yahmadi et al. (2021), who conducted a comparative study on the efficiencies of traditional FMECA and fuzzy-based FMECA. The study considers Solar gel battery manufacturing defects as the case study. A holistic risk measurement from source to tap of a water supply system has been carried out by Haider et al. (2021), where an integrated FTA-based Fuzzy-FMEA approach has been applied. An upgradation of the previous study, i.e. Fuzzy-FMEA approach, has been provided by García Aguirre et al. (2021), where the conventional Fuzzy set has been replaced by Pythagorean Fuzzy Sets (PFS). The said researchers have studied Pythagorean Fuzzy Dimensional Analysis (PFDA) based FMEA approach and its application. The concept of fuzzy aggregation in the field of FMEA has been observed in the literature (Yazdi, 2018), where the judgment of several experts has been accumulated using this approach, and the final RPN has been generated from the accumulated results. Finally, those results have been compared with the traditional results. A novel risk assessment framework of maritime cyber threats has been studied by Park et al. (2023). They combine FMEA with a rule-based Bayesian network for risk level evaluation of identified threats. Application of the modified FMEA approach has also been observed in the Industry 4.0 domain (Salah et al. 2023), where a yoghurt-filling system under the Industry 4.0 environment has been considered as a case study. The FMEA tool has also been combined with Fault Tree Analysis (FTA) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) method, an MCDM technique used for assessment of the Reliability level of the production technology at a carousel-type production line in the production of a plastic component (Bujna et al. 2024).

3.2.2 Weightage assessment methods and their application in various environments

Durmić et al. (2020) used the Full Consistency Method (FUCOM) to evaluate the weights of criteria in a sustainable supplier selection problem. Kumar et al. (2022) employed the Stepwise Weight Assessment Ratio Analysis (SWARA) model to assign weights to different criteria in a Spray-Painting Robot Selection problem. Panchal et al. (2022) utilized the traditional Analytic Hierarchy Process (AHP) for landslide hazard assessment, specifically to determine the weights of causative factors. Pramanik et al. (2022) developed an innovative model called the Objective-Subjective Weighted method for Minimising Inconsistency (OSWMI), which they applied in a web service selection case study. Das et al. (2023) adopted the Shannon entropy method for evaluating criteria weights in diamond-like carbon (DLC) coating selection. Mohata et al. (2023) used the Criteria Importance Through Intercriteria Correlation (CRITIC) method to select a passenger vehicle. These methods are generally effective when sufficient data are available; in cases of limited data, alternative strategies are used. For example, Das et al. (2012) applied the Fuzzy-AHP method to assess criteria weights for evaluating technical institutions in India. Zavadskas et al. (2018) introduced the Rough Set-based SWARA (R-SWARA) method to determine weights under uncertainty, applying it in a logistics study. This approach has inspired many researchers, including Tanackov et al. (2022) and UZGÖR et al. (2024).

3.2.3 Different MCDM techniques and their application in different environments

The concept of Rough-based Technique for Order Preference by Similarity to Ideal Solution (R-TOPSIS) method has been adopted for ranking assessment of failure modes (Wan et al. 2019). This study is also involved with FMEA, where a new criterion, i.e. Environmental Factor (E), apart from S, O, and D, has been introduced. TOPSIS is a versatile MCDM technique that has been considered by many scholars for inclusion with FMEA or FMECA in various domains for the evaluation of failure mode ranking, e.g. the Rough TOPSIS (R-TOPSIS) operation has been adopted by Song et al. (2014) for FMEA analysis of a steam valve system under an uncertain environment. Carpitella et al. (2018) utilised FMECA-based Fuzzy-TOPSIS (FTOPSIS) operation for optimisation of maintenance activities of a complex system. Apart from TOPSIS, some other MCDM techniques have also been employed with FMEA, such as a Fuzzy-VIKOR-based FMEA approach has been adopted by Safari et al. (2016) for assessing enterprise architecture risks. On the other hand, Ghoushchi et al. (2021) have proposed an extended SWARA-MOORA-oriented FMEA method, which is based on Z-number theory for risk prioritisation. An attractive idea of a Hybrid MCDM-oriented FMEA approach has been proposed by Kuchekar et al. (2024), where the Industrial Pressure Relief Valve has been used for failure mode evaluation and its ranking assessment. Apart from those MCDM techniques, a new technique named the Reference Ideal Method (RIM) has been introduced by Cables et al. (2016), and they mentioned its merits over the conventional MCDMs. This method has been applied by Das et al. (2023) for the selection of DLC coating, and the result has been found superior compared to the TOPSIS method due to the appropriate selection of range and reference ideal value, based on which the method has been applied. To apply the MCDM technique under a vague environment, Cables et al. (2017) have introduced the Fuzzy set-based RIM (FRIM) methodology as well as elaborated it through an example.

The said methodology has been applied by Sánchez-Lozano et al. (2020) for military advanced training aircraft selection, and the result has been found quite impressive, though the limitations of the method have also been discussed. In order to get better outcomes, the range of the criteria should be considered with adequate caution. The upgradation of FRIM has also been proposed by Cables et al. (2020), where the authors have integrated the Pythagorean fuzzy numbers with RIM and observed the outcome with an application.

3.3 Maintenance of an IoT-based WDCS using the FFTA-RCM combined approach

3.3.1 Fuzzy Fault Tree Analysis (FFTA)

Kang et al. (2019) adopted FTA to find failure characteristics of semi-submersible floating offshore wind turbines. Both quantitative and qualitative assessments of the failure characteristics have been performed. Chi et al. (2014) investigate the causes of fatal falls in the Taiwanese construction industry through FTA. They established a causal relationship among the events that cause accidents. Fazlollahtabar et al. (2018) proposed an FTA-RBD-based integrated model for the reliability calculation of an Automated guided vehicle (AGV) operating under a complex manufacturing system. This study has also evaluated system reliability of the manufacturing system using the minimal path and cut method (MPCM). Gachlou et al. (2019) use FTA for risk assessment of a river basin to investigate undesirable events. In their work, the failure probability of the top events has been computed. Makajic-Nikolic et al. (2016) apply the FTA method for risk assessment associated with infectious medical waste management. Chen et al. (2017) proposed a method for fault diagnosis of an IOT system using FTA and fuzzy neural network (FNN). FNN is used to train the relationship mapping between fault symptoms and faults. But in real-life situations, due to a shortage of useful failure data, the analysis of the effective life of a system becomes very difficult. Under this uncertain environment, fuzzy set theory performs a key role by extracting calculable essence from qualitative data based on this idea. The idea of this theory was proposed by Prof. L. A. Zadeh (1965). Liu et al. (2015) in their study, conducted an FTA of high-speed railway accidents. A fuzzy set theory has been applied to their research work to overcome the uncertain characteristics of basic events in fault trees caused due to obscure information. Henceforth, this theory is considered a worthy choice for the computation of qualitative data resulting from FTA, and combining those studies, the concept of FFTA comes into the picture. Mahmood et al. (2013) introduce a review of FFTA and reflect on its strengths, weaknesses, and application in their research work. Yazdi et al. (2017) used FFTA to evaluate the failure probability (FP) of various basic events (BEs) in a chemical storage tank located at a chemical plant. Three experts from the respective field have been invited to provide qualitative information regarding the failure of basic events. Badida et al. (2019) utilized FFTA to evaluate the FP of pipelines associated with oil and natural gas pipeline systems using expert opinion. Babaei et al. (2018) performed FFTA of agricultural water conveyance and delivery systems to compute the FP of top events. Abdelgawad et al. (2011) apply FFTA to the construction industry. A case study has been conducted on horizontal directional drilling in this regard. Kargar et al. (2022) studied the risk assessment of the Asymmetric Tandem Lifting operation on the basis of FFTA. Gürgen et al. (2023) have considered FFTA to identify the root causes of accidents resulting from the loss of a ship's steering ability. Khajuria (2023) has proposed FFTA on a Non-Repairable system that contains uncertain information. Triangular intuitionistic fuzzy numbers (TIFNs) have been used for data uncertainty.

3.3.2 Reliability Centered Maintenance (RCM)

RCM methodology puts in the preventive maintenance action in a structured manner to extend the service life of the system. The concept, along with a detailed methodological overview of RCM, has been presented by Tale (2019). The author has constructed a flow diagram of RCM methodology during this research work, which was found very helpful during this study. This method found a unique paradigm over other maintenance strategies and was adopted in different engineering fields. Aji et al. (2023) applied the RCM method on an onboard communications-based train control device and found this method useful. Fang et al. (2019) applied the RCM technique to the metro door system. Firstly, the sub-systems and their components have been identified. An RCM logic decision diagram has been set up, and based on the diagram, the maintenance mode of each subsystem has been chosen. Eriksen et al. (2021) examined the applicability of RCM on Unmanned autonomous cargo ships. The limitations and necessary amendments of the RCM have been discussed in the article. Patil et al. (2022) developed an optimised maintenance program using RCM. They choose steam boiler systems as their working domain. Implementation of RCM implies the reduction of maintenance costs by improving the Availability of the system. The RCM framework was also applied to distribution grids by Wang et al. (2023) based on FTA. This study was found quite helpful because of the integration between RCM and FTA. Suryono et al. (2018) considered the RCM technique to find the optimal inspection frequency, PT. X used an automated machine. The average inspection time and average repair time based on a fixed reliability value have been computed based on the said method. Based on the RCM technique, Setiawan et al. (2019) were able to increase fabric production by 13% by reducing downtime by up to 30% of an Air jet loom (ALJ) machine. The above literature reviews signify the effectiveness of RCM in finding effective maintenance strategies based on the failure probability of the system as well as in minimizing downtime, which signifies the improvement of system availability. Taha et al. (2023) proposed a cyber-physical system on electric buses to deal with the challenges of developing self-improvement and online risk control. The base of the online risk control approach used in this study is RCM, which has been used for the enhancement of system uptime. Taha et al. (2023) proposed a cyber-physical system for electric buses to address the challenges of developing self-improvement and online risk control. The base of the online risk control approach used in this study is RCM, which has been used for the enhancement of system uptime. Shaheen et al. (2022) conducted a literature review focusing on Industry 4.0 and its effect on maintenance management systems. Tortorella et al. (2021) have examined the impact of integrating Industry 4.0 on Total productive maintenance.

3.4 Diagnosis and prognosis of an IoT-based WDCS using BN-ARIMA combined Model

3.4.1 FFTA and Fermatean Fuzzy Set (FFS)

A detailed literature review of FFTA has already been discussed in section 3.3.1. Apart from that, Akhtar et al. (2022) conducted FFTA on Wind energy systems to find out the system's reliability. Risk analysis based on the fuzzy risk index (FRI) has been applied to identify the impact of BEs on Top events (TE). Mentes et al. (2011) use FFTA on spread mooring systems for fault diagnosis and hazard estimation. Sensitivity analysis has been carried out to identify the importance and impact of BEs on TE. All the said research work on FFTA indicates the transformation of ambiguous failure data into its crisp value using expert judgments. This is quite useful in the absence of proper quantitative data. The concept of Fermatean fuzzy set (FFS) has been proposed by Senapati et al. (2020). The fundamentals of the research work have been inspired by Intuitionistic Fuzzy set (IFS) (Atanassov,1986) and Pythagorean Fuzzy sets (PFS) (Yager,2013). The FFS has been preferred over IFS and PFS due to higher nonstandard membership grades. De et al. (2000) have shown some basic operations on IFS. Kabir et al. (2019) analyse the failure probability (FP) of the events connected to fuel distribution of a ship using IFS-based temporal fault tree analysis. Yazdi et al. (2023) have conducted the Reliability analysis of a process system with the help of IFS. Different methods, such as Failure Mode and Effects Analysis, BN and FTA, are incorporated in the work. Yousofnejad et al. (2024) have evaluated the Reliability of an oxygen supply system with the help of IFS-based FTA. Based on the study, the idea of adaptation of FFS for FTA has been stimulated. The concept of FFS has been utilized in different fields such as decision-making problems (Simić et al.,2022), multi-objective transportation problems (Akram et al.,2023), etc.

3.4.2 Fault Diagnosis

After the evaluation of FP, the fault diagnosis of the system has been carried out. The approaches in connection with fault diagnosis processes are primarily based on Model-Based, Knowledge-Based, and Pattern Recognition approaches (van Tung et al.,2009). The pattern recognition-based approach is quite complex, as it is achieved by the classification of signals based on the information and features extracted from the signals. A complete overview of the Model-based system and Knowledge-based system has been provided by Li et. al. (2020). On the other hand, A review on Model-based fault diagnosis of the dynamic system has been presented by Ekanayake et. al. (2019). The advantages of BN have been portrayed by Cai et. al. (2017). Based on the following literature survey, the assumption has been drawn in favor of BN for acting as a fault diagnosis tool along with FFTA. During the study, it was found that the integrated approach of FTA and BN has a lot of applications in various fields for fault diagnosis. He et al. (2019) has proposed a BN model-based FMEA/FTA approach for fault diagnosis of rub-impact fault of a 600MW turbocharger. The fault diagnosis of a Safety Instrumented system has been evaluated using FTA-based BN (Chiremsel et al.,2016). The diagnosis importance factor of each component has been evaluated by converting FTA into equivalent BN. Jinfei et al. (2021) have integrated both BN and FTA to handle the uncertainties in fault diagnosis of heavy CNC machines. Sakar et al. (2021) analyzed risk by mapping FTA into BN. They have considered grounding accidents as a case study. A BN-based FTA has been adopted for safety evaluation by Liu et al. (2010) on a coalmine haulage system. Babbio et al. (2001) applied FTA mapping on BN to analyze dependable systems. This article has provided a framework for mapping FT into BN. However, in the case of qualitative failure values, an integration of FTA with fuzzy set theory has been applied along with BN for fault diagnosis. Soltanali et al. (2021) have proposed an integrated FFTA-BN-based maintenance optimization of complex equipment, which falls under the automotive manufacturing domain. In this study, the BN has been constructed by the failure probability of BEs, which FFTA evaluated. Jafari et al. (2020) evaluated the reliability of fire alarm systems using dynamic BN-FFTA combined analysis. Cheng et al. (2022) experimented with fault diagenesis on a flywheel using the FFTA-belief rule-based approach. BN has acted as a bridge between FFTA and the Belief rule.

3.4.3 prognostic models for RUL estimation

A details overview of different RUL prediction approaches has been given by Sikorska et al. (2011) and van Tung et al. (2009). Based on the overview, a survey on different RUL prediction approaches has been carried out. Tian et al. (2010) developed an Artificial neural network approach for predicting remaining useful life. Both failure and suspension histories are taken into consideration to obtain better results. A deep learning model has been proposed by Arunthavanathan et al. (2021) for failure prognosis. Yan et al. (2004) developed a prognostic algorithm to assess machine performance and remaining useful life. Machine performance assessment has been done using logistic regression analysis followed by the ARMA model to evaluate the remaining useful life of the components. Ali et al. (2015) proposed a method combining ANN and Weibull distribution for the calculation of the remaining useful life of a bearing. Kundu et al. (2019) presented a Weibull Accelerated Failure Time Regression model for predicting remaining useful life. Banjevic et al. (2006) calculate the reliability function and remaining useful life using the Markov failure time process. The real-time life of the equipment has been predicted by Tan et. al. (2017) using an optimized ARMA model. The ARIMA time series algorithm has been applied by Lu et. al. (2020) for RUL prediction of Lithium-ion Batteries. The ARIMA model has been used along with Response surface methodology for the prediction of bearing service life (Ammar et al. 2022). Apart from RUL estimation, the ARIMA model has been portrayed as an effective forecasting tool and used in different domains like Short-term wind speed forecasting (Grigonytė et al. 2016), Consumer Price Index forecasting (Mohamed, 2020), etc.

3.5 Summary of systematic literature review

A broad literature review of the research work has been conducted in this section. Various domains have been attached to the study. Based on the complete results of the review, a summary has been chalked out, where some impactful literature has been sorted out and addressed, and non-addressed issues have been discussed in a tabulated form.

Sl. No.	Literature	Issue Addressed	Issue Not Addressed
1.	Herrmann (2018)	Potential risks of a smart factory	Inadequate addressing of the effective remedies.
2.	Kumar et. al. (2020)	Reliability analysis of a communication system using a Markov model	The availability and Maintainability analysis has not been done.

3.	Zhao et. al. (2016)	Application of an entropy-based Markov model on a Hybrid multi-carrier energy system	The effect of the uncertain environment has not been incorporated in the study, i.e. application of Fuzzy or allied approach on the model.
4.	Chang et al. (2015)	Fuzzy-based reliability assessment of a labour-intensive manufacturing system	Fuzzy-based Availability and Maintainability of the system have not been addressed.
5.	Balaraju et al. (2019)	Fuzzy-based FMEA approach for risk assessment of a Load-Haul-Dumper (LHD) Machine.	The concept of Membership function and non-membership function has not been incorporated.
6.	Salah et al. (2023)	FMEA of the yoghurt-filling system under the Industry 4.0 environment	Studies under an uncertain environment have not been addressed.
7.	Song et al. (2014)	FMEA analysis of a steam valve system using R-TOPSIS.	Environmental effect and cost factor criteria have not been considered.
8.	Zavadskas et al. (2018)	Introduction of the Rough Set-based SWARA (R-SWARA) method to determine weights under uncertainty	Not incorporated with any MCDM approach, as well as FMEA, for studying the outcome of the combined model.
9.	Das et al. (2023)	Application of RIM for the selection of DLC coating.	The vague environment and its respective tools have not been implemented.
10.	Fazlollahtabar et al. (2018)	FTA-RBD-based integrated model for the reliability calculation of an AGV	Availability and Maintainability, and overall RAM analysis have not been conducted.

11.	Yazdi et al. (2017)	Failure probability of various basic events in a chemical storage tank located at a chemical plant	The concept of the non-membership function has not been considered.
12.	Khajuria (2023)	FFTA on a non-repairable system using Triangular intuitionistic fuzzy numbers.	Instead of TFN, no other such as Trapezoidal Fuzzy number has been considered.
13.	Fang et al. (2019)	Application of the RCM on a metro door system	FTA of the system have not been incorporated.
14.	Wang et al. (2023)	RCM of distribution grids based on FTA	The concept of uncertainty has not been addressed.
15.	Senapati et al. (2020)	The fundamentals of the FFS	The application of the concept to failure analysis has not been provided.
16.	Yousofnejad et al. (2024)	Reliability evaluation of an oxygen supply system with the help of IFS-based FTA	BN-based fault diagnosis or any other allied method has not been incorporated.
17.	Sakar et al. (2021)	Risk analysis by mapping FTA into BN	The concept of vagueness has not been addressed.
18.	Soltanali et al. (2021)	Integrated FFTA-BN-based maintenance optimization of complex equipment	The concept of a non-membership function in FFTA has not been considered.
19.	Banjevic et al. (2006)	Calculation of the reliability function and remaining useful life using the Markov failure time process.	The concept of an uncertain environment has not been taken into consideration.
20.	Lu et. al. (2020)	Application of the ARIMA time series algorithm for RUL prediction of Lithium-ion Batteries	Fault diagnosis of the system has not been covered in the article.

Table 3.1 Summarised table of systematic literature review

Chapter 4

Gap Analysis

4.1 Introduction

Gap analysis identifies gaps between the optimized allocation and integration of the inputs (resources) and the current allocation level. This reveals areas that can be improved. It involves comparing actual performance with expected performance to pinpoint weaknesses and opportunities for growth. By understanding the gap, organizations can create action plans to bridge it and achieve their goals. Similarly, Gap analysis in research refers to identifying and assessing the differences between the current state of a topic and its desired state, or the gaps in existing knowledge or research. It helps pinpoint areas where more research is needed, where current research has conflicting findings, or where there's a lack of evidence to support a claim. In this research, some gaps have been observed during literature reviews:

- Reliability assessment of some Industry 4.0 domains under the vague environment.
- A comparative analysis of FMEA results for a smart system.
- Reliability-based maintenance work of any IoT device in an uncertain environment.
- Remaining life estimation of IoT devices using expert elicitation.

The knowledge gap has been bridged by prior art and state of the art, highlighting the direction and magnitude of the present investigation and inquisition.

4.1.1 Aim of the present investigation

The aim is a broad, general statement of what we hope to achieve with a project or research study. It provides the overall direction and purpose. The prime aims of the study focused on:

- User-friendly as well as environmentally friendly smart systems in the Indian ecosystem.
- Upgradation and upliftment of the quality of life from an Indian perspective.
- Well-being of the Indian society.

4.1.2 Objective of the research work

Objectives are specific, measurable, achievable, relevant, and time-bound statements that break down the aim into smaller, actionable steps. The key objectives of the research work have been pointed out and described below.

1. To evaluate the Reliability as well as availability of a system concerning the Industry 4.0 Domain under an uncertain environment.

2. To identify the probable failures of a system and rank them according to their severity.
3. To locate the critical components of the system and adapt proper maintenance strategies.
4. To evaluate the remaining useful life of the concerned components.

4.1.3 Scopes of the present work

Lastly, the scope of the research work emphasises the collection of data from allied industries as well as observing the current scenario of Industry 4.0 in India and acting according to the present condition. The prime scopes of the research work are limited to the following domains and systems:

- AN IoT-based Weight data communication system for defining its maintenance strategy as well as its remaining useful life, which has been considered from an Aluminium smelting plant under an Indian industry.
- A smart Arsenic-Iron removal plant for its Failure Mode and Effects Analysis, and the case study has been taken from a Water purifying plant located in the Eastern part of India.
- A theoretical Smart factory architecture as envisaged by one renowned Indian researcher for its reliability and availability assessment under a vague environment.

Considering the scopes and objectives, a holistic approach has been taken to maintain a secure and sustainable operating condition, as well as to provide a robust maintenance policy of an Industry 4.0 architecture.

Chapter 5

Reliability & Availability Assessment of Industry 4.0 under an Uncertain Environment

5.1 Introduction

The journey of the modern Industrial Revolution began with the invention of the steam engine. Today, it continues in the form of Industry 4.0, integrating advanced sensors, software, wireless networks, Artificial Intelligence, and more (Rudiyanto et al., 2020). In this era, the concept has gained rapid attention due to its contribution to sustainable economic, environmental, and social development. Within this domain, smart sensors and actuators, along with various intelligent machinery and interconnected computers, communicate among themselves, interact with the environment, and make decisions with minimal human intervention (Ghobakhloo, 2020). Modern technologies such as the Internet of Things (IoT) / Industrial Internet of Things (IIoT), Cloud & Big Data, Cyber-Physical Systems (CPS), Advanced Robotics, Simulation and Digital Twins, Additive Manufacturing, Virtual Reality (VR), Blockchain, etc., are now essential components of this domain and serve as its backbone (Efthymiou et al., 2021). The core principle of Industry 4.0 is to collect data from different parts of the value chain. Data collection is fast, flexible, and efficient, focusing on gathering and analyzing data with computerized machines to reduce production costs while improving quality. CPS and IIoT play vital roles by enabling data collection from the real world along with processing and storage operations (Fernández-Caramés et al., 2021). The Internet of Things aims to provide a comprehensive digital daily life by connecting smart devices and gadgets, allowing them to interact and cooperate to offer easier and quicker solutions for everyday challenges. For example, modern domestic air conditioners now come equipped with built-in Wi-Fi chips, enabling control from anywhere, even outside the home. The only requirement is connecting the AC to the home Wi-Fi router, facilitating direct internet access. The concept of IIoT is similar to IoT, but its applications focus on manufacturing processes, services, retail businesses, and more. IIoT implementation is intended not only for machine-to-machine communication but also for bridging the gap between physical and digital assets within a factory and reducing human-machine cooperation through smart automation and machine learning. Adding intelligence to machine tools within a production chain enables factories to adapt, increasing flexibility to meet industrial and client requirements. From a manufacturing perspective, this domain can be seen as a smart and intelligent manufacturing network that integrates production facilities, warehouse systems, logistics, and social needs to establish a global value creation network (Shi et al., 2020). The concept of the smart factory, along with its associated benefits and limitations, is depicted below.

5.1.1 Smart Factory

The concept of Smart factory has been irradiated from the context of intelligent manufacturing to achieve advanced manufacturing on the basis of network technologies and manufacturing data (Chen et. al.,2017). A general definition of smart factory has been provided by Mabkhot et. al. (2018), in their study and quoted as *"A manufacturing solution that provides such flexible and adaptive production processes that will solve problems arising on a production facility with dynamic and rapidly changing boundary conditions in a world of increasing complexity. This special solution could, on one hand, be related to automation, understood as a combination of software, hardware and/or mechanics, which should lead to optimization of manufacturing resulting in reduction of unnecessary labor and waste of resource. On the other hand, it could be seen in a perspective of collaboration between different industrial and nonindustrial partners, where the smartness comes from forming a dynamic organization"*. The prime requirements of a smart factory architecture have been tabulated in Table 5.1. The complexity and criticality of such technology could be understood from the table.

Req. No.	Requirements	Brief Explanation
1	Modular machine tools or workstations	Flexibility of machines and work stations to be redesigned for changing the shop floor layout and adjustment of process function.
2	Modular material handling equipment	Reconfiguration of material handling equipment or changing of equipment capability on the shop floor to transfer the required product.
3	Standard communication and CPS	Recording and enrichment of information in the integration layer through a standardized communication protocol
4	Sharing meaningful information	Sharing and reusing of data across various applications, enterprise and factory boundaries under a common framework
5	Modular and decentralized control Architecture	Automatic uploading of the control module into the physical module from the cloud without human intervention
6	Virtual interfaces with CPS	Necessary interfaces that retrieve and store necessary information from CPS, enabling online simulation and diagnosing assistance.

7	Cloud computing	Sharing of information regarding factory functions and product services over cloud computing
8	Online data analysis	Converting the customer requirement into a product using existing resources or outsourcing services.
9	Customization and real-time capability	Ability to respond in real time and for manufacturing to order even a single unit.
10	Online monitoring and control	Monitoring and controlling of system in real time using reactive decision making and diagnostic

Table 5.1 Prime requirements of smart factory

This environment facilitates collaboration between human and production processes on one side, and intelligent, computer-based systems on the other. These systems ensure a seamless, continuous flow of the production process, enhancing performance and quality (Osterrieder et al., 2020). Wang et al. (2016) have discussed the architecture of the smart factory as illustrated in Fig. 5.1, which consists of four layers: Physical, Network, Cloud & Intelligence, and Terminal. Brief descriptions of each layer are provided below.

i) Physical Layer

This layer consists of various physical equipment which used to acquire real-time information from the production line and communicates among them through an industrial network to achieve a system-wide goal. Intelligence levels of the said equipment are enhanced up to the requirements of IoT for smart operation.

ii) Network Layer

Different kinds of communication through industrial networks, such as Industrial wireless sensor networks, take place under this layer. It not only enables inter-artefact communication, but also transmits the information from the physical layer to the Cloud & Intelligence Layer and vice versa. Various modern technologies, such as software-defined networks (SDN) and device-to-device communication (D2D), are incorporated under this layer for reliable communication and cooperation among equipment.

iii) Cloud & Intelligence layer

Cloud is described as servers that are connected over the internet to access the software and database that run on those servers. Using such technology, the internet can be virtualized as a huge resource pool. From that perspective, it provides a better solution for handling big data so that both the storage space and intelligence can be utilized on demand. It analyzed the semantics of various data and provided the ability for self-organization, self-learning, and self-adaptation. Moreover, it provides the basis for decision-making and hints towards design optimization and active maintenance.

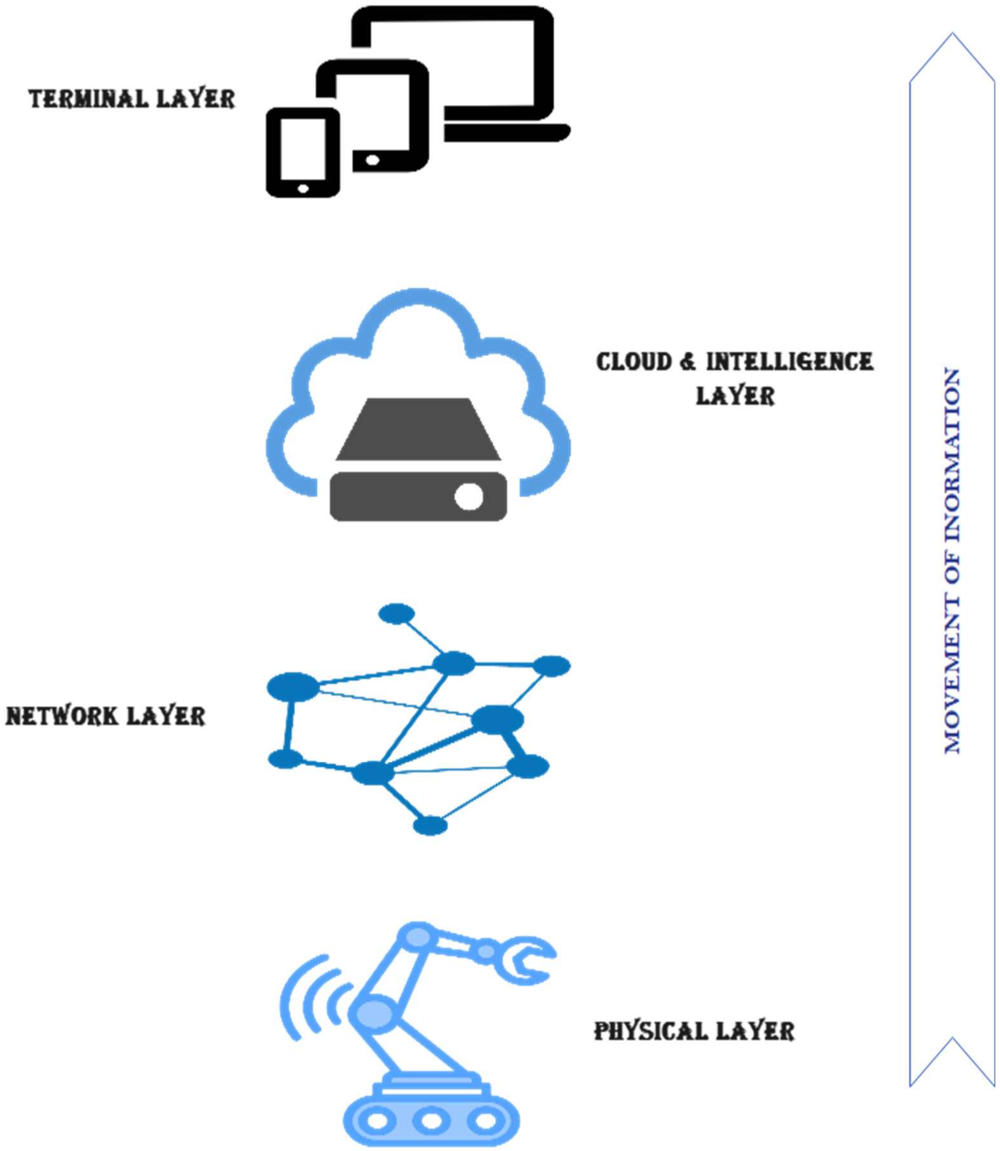

Fig. 5.1 Architecture of smart factory

iv) Terminal Layer

It is the layer through which people can interact with the smart factory. The experts can access the statistical and other informative data provided through the Cloud & Intelligence layer on the terminals such as computers, tablets, mobiles, etc., to carry out maintenance tasks or other diagnostic actions.

The essential characteristics of the smart factory have been discussed below. This characteristic has displayed the superiority of the said architecture over the conventional one.

- Monitors, collects, coordinates, controls, and integrates data by using IT communications along with data management technology.
- Rapid Production and distribution of manufactured goods in response to market demand.
- Efficient operability using intelligent agents and other cyber-physical systems.
- Optimizing complex production decisions using automated agents.
- Use of digital connectivity to collaborate with suppliers, customers, partners, and departments within the facility.
- Ability to be connected with a global network of similar production systems and the digital supply chain.

From the above discussion, it is clear that the concept of the smart factory system is quite intricate and sophisticated. As the orientation of the layers lies in series, Minor failure of any elements in any layers causes the entire system failure. Under these circumstances, the elements have to be reliable enough to continue the system operation smoothly, and that is why the reliability assessment is an essential criterion for any industry. The theoretical idea of reliability and its calculation has been provided in the reference book of Shrinath, L. S. (1991) and from that study, it can be concluded as the probability of an element or system performing its usual function for a specified period of time under a predefined environment. This phenomenon is helpful for the maintenance activity of the system. In order to derive the value of reliability for any system over a specified time, different failure data of the said system have to be known. Failure rate (λ) and repair rate (μ) are the prime constituents for the enumeration of the reliability of a repairable system. It might be constant or variable, and different mathematical models have been employed for reliability calculation depending upon the nature of the λ, as shown in different literature (Shrinath, L. S. 1991 & Billinton et al. 1992). In the current study, the value of λ has been considered as constant based on experts' opinion. In certain circumstances, exact failure data are not available due to various reasons, such as improper storage of failure data, the policy of the machine manufacturer, etc. In such cases, experts' elicitation based on their observation plays a key role in order to trace out such factors. But the matter of concern is the nature of the data, which is qualitative in nature. The essence of such data is retrieved using fuzzy set theory (Zadeh, L. A., 1965). After computation of such factors of each component or sub-systems, Reliability assessment of the entire system is performed and there are several methods available for reliability calculation, such as, reliability block diagram, Fault tree analysis (FTA) (Liu et. al., 2015), Tie set and cut set method, Markov chain analysis (Kumar et. al., 2020), etc. The Markov analysis is a suitable technique for reliability assessment of a repairable system (Billinton et. al., 1992). A brief description of Markov analysis is mentioned below for a better understanding of the research work.

5.1.2 Fundamentals of Markov analysis

Markov analysis is a probabilistic technique that provides probabilistic information for decision-making in a respective domain. This approach can be applied to the random behaviour of the system, which may vary discretely or continuously w.r.t time and space. The probabilistic information implies that the future state of the system will strictly depend upon the present state of the system instead of the past condition. A popular application of the Markov analysis is customer brand switching. In such a case, suppose there are two brands, A and B. Now the governing organization of A identify the sales of their brand along with the switchover of the sales from A to B and vice versa. Based on the analysis, a transition matrix is generally developed to analyze the probability of periodic switch over and act according to the situation. Suppose for a certain month, it has been analyzed by the experts that the switching of brand A to B is 30% and from B to A is 20%. Then it can be represented by a diagram as a two-state system.

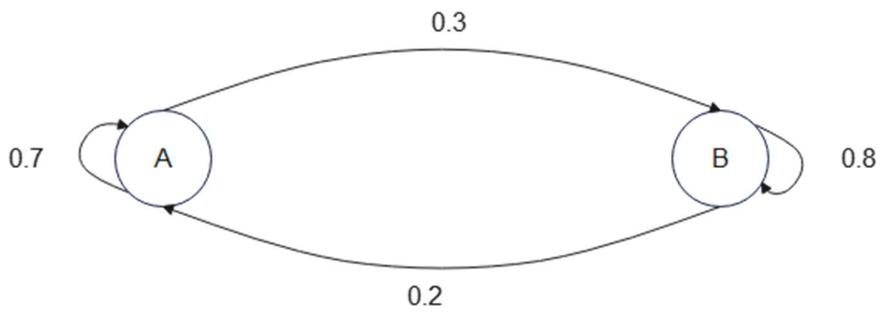

Fig. 5.2 A two-state system

Based on the Fig. 5.2, a transition matrix has been developed. This matrix is the heart of the Markov analysis.

Transition matrix of the brand switching: $\begin{bmatrix} Brand & A & B \\ A & 0.7 & 0.3 \\ B & 0.2 & 0.8 \end{bmatrix}$

Using this matrix, the organization can easily identify the trend of the switchover and can predict the future of the market. Likewise, the reliability assessment of the system can be easily evaluated using this method. The details method of reliability assessment has been studied and adopted from chapters 8 and 9 of Billinton et al. (1992). It has been found effective for reliability assessment of a repairable system, and that is why it has been applied in the following case study. The Entropy-based Markov chain model has been used for this case study, where a fusion process has been employed on reliability results to obtain a consensus output (Zhao et. al., 2008).

5.2 Methodology

The research work has been conducted in four steps. All steps are discussed with proper mathematical explanations.

5.2.1 Construction of state space diagram

A state space diagram is the basis of Markov analysis. It is used to identify the probable states that a system may achieve due to the individual state of each component. For every component, there are two states: either active or failed. The useful calculation for figuring out the number of states (S) for a system with n components can be written as:

$$S = 2^n \tag{5.1}$$

In this problem, we have considered the entire smart factory as a system and each layer as a component. So, we can identify that the total number of states of the system is 16, and the diagram is shown in Fig. 5.3. P1 to P16 are known as the availability, where availability is a function of Reliability and Maintainability of the respective state. P1 can be portrayed as:

$$P1 = \frac{\mu1*\mu2*\mu3*\mu4}{(\lambda1+\mu1)(\lambda2+\mu2)(\lambda3+\mu3)(\lambda4+\mu4)} \tag{5.2}$$

In the same way, the P16 can be written as:

$$P16 = \frac{\lambda1*\lambda2*\lambda3*\lambda4}{(\lambda1+\mu1)(\lambda2+\mu2)(\lambda3+\mu3)(\lambda4+\mu4)} \tag{5.3}$$

The availability of a state can be defined in a general way as:

$$Availability = \frac{Up\ time\ of\ a\ respective\ system}{Total\ time\ of\ operation} = \frac{Up\ time}{Up\ time + Down\ Time} \tag{5.4}$$

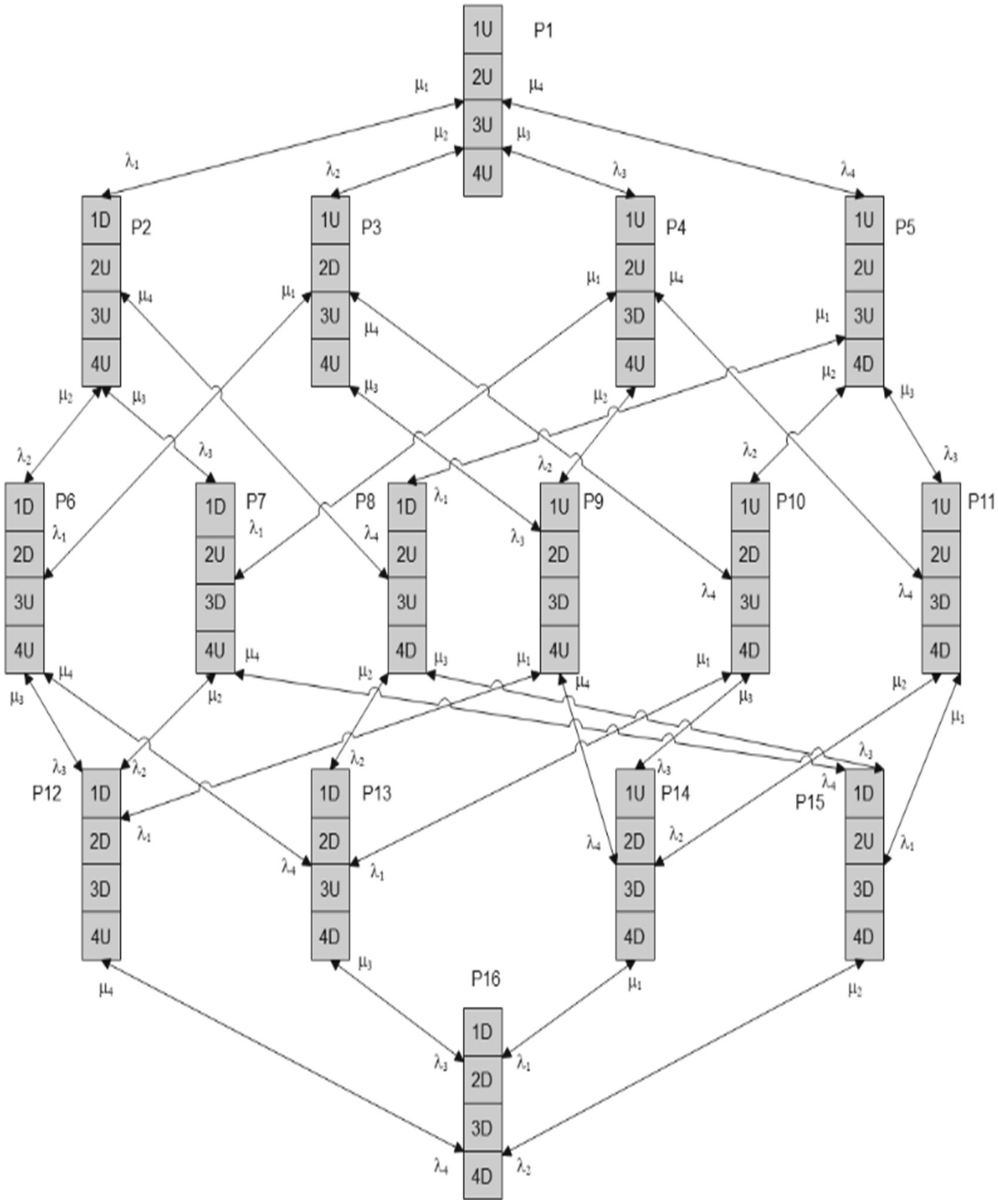

Fig. 5.3 State space diagram of the Smart Factory system

This signifies that the incoming entities in the above probability blocks are multiplied together in the numerator for the probability calculation of the states. In a similar way, the other 14 states are calculated. It has to be noted that the system is in a series configuration. That's why the failure of any one layer may lead to system failure. Under these circumstances, individual reliability assessment of each layer is essential. The logic gate diagram of Availability (A), Reliability (R) and Maintainability (M) is shown in Fig. 5.4. Required failure data for reliability assessment has been investigated in the next step.

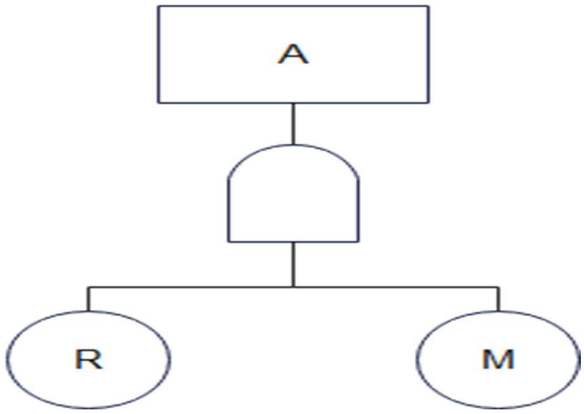

Fig.5.4 Relationship Among Availability (A), Reliability (R) and Maintainability (M)

5.2.2 Investigation of failure data using Fuzzy Set theory

The concept of the smart factory is unique, and access to such technologies is restricted to a certain extent. To accumulate the required failure data by overcoming such situations, the ideology of the experts from the respective field has been adopted. Three experts from related fields have been invited for their valuable outlook regarding the linguistic measurement of MTTF and MTTR of the system and the layers. Based on their opinions and comments, a list of justified linguistic variables and their respective Triangular Fuzzy Number (TFN), along with a suitable scale, has been chosen. The weightage of the experts has been evaluated by considering the data provided in Table 5.2. The details description of the experts along with their respective scores has been displayed in Table 5.3.

Sl. No.	Particulars	Category	Score
1.	Post Held	HOD / Professor / Chief Scientist	4
		Associate Professor / Principal Scientist	3
		Assistant Professor / Scientist	2
		Lecturers / Research Fellow	1
2.	Experience	Over 25 Years	4
		More than 15 Years & less than 25 Years	3

		More than 5 Years & less than 15 Years	2
		Below 5 years	1
3.	Academic Merit	PhD and Above	4
		M.E/M. Tech	3
		B.E/B. Tech	2
		Diploma	1
4.	Research Work Involvement (Hours / Week)	More than 40	4
		More than 25 & less than 40	3
		More than 10 & less than 25	2
		Less than 10	1

Table 5.2 Categorical Ratings of the Experts

Expert (E)	**Designation**	**Job/Research Experience**	**Qualification**	**Time of involvement**	**Assign Score (x_i)**
E1	Professor (Production Engineering) (Score: 4)	27 Years (Score: 4)	PhD (Score: 4)	7 Hours/ Week (Score: 1)	13
E2	Scientist (Quality Control) (Score: 2)	7 Years (Score: 2)	PhD (Score: 4)	28 Hours/Week (Score: 3)	11
E3	Research Fellow (Project Work) (Score: 1)	7 Years (Score: 2)	M. Tech (Score: 3)	45 Hours/ Week (Score: 4)	10
		Sum of Assigned Score ($\sum x_i$)			**34**

Table 5.3 Detailed description of the Experts

Based on their individual and sum-assigned scores, the weightage has been calculated and reflected in Table 5.4.

Expert (E)	E1	E2	E3
Weightage $\left(\frac{x_i}{\sum x_i}\right)$	0.382353	0.323529	0.294118

Table 5.4 Weightage of Experts

The linguistic variables and their corresponding TFN for MTTR and MTTF are given in Tables 5.5 and 5.6, respectively. TFN has been used in this study due to its simplicity as well as effectiveness. Those values have been considered based on expert advice.

Sl. No.	Linguistic Variables	TFN
1	Excellent (E)	(0, 0, 25)
2	Good (G)	(0, 25, 50)
3	Moderate (M)	(25, 50, 75)
4	Bad (B)	(50, 75, 100)
5	Not Desirable (ND)	(75, 100, 100)

Table 5.5 Linguistic variables and their corresponding TFN for MTTR

Sl. No.	Linguistic Variables	TFN
1	Intolerable (I)	(0, 0, 1000)
2	Not Desirable (ND)	(0, 1000, 2000)
3	Very Bad (VB)	(1000, 2000, 3000)
4	Bad (B)	(2000, 3000, 4000)
5	Average (A)	(3000, 4000, 5000)
6	Good (G)	(4000, 5000, 6000)
7	Very Good (VG)	(5000, 6000, 7000)
8	Excellent (E)	(6000, 7000, 8000)
9	Outstanding (O)	(7000, 8000, 8000)

Table 5.6 Linguistic variables and their corresponding TFN for MTTF

The linguistic representation of MTTR and MTTF by considering the expert's opinion for each layer has been tabulated in Tables 5.7 and 5.8, respectively.

Factors	E1	E2	E3
$MTTR_1$	M	M	G
$MTTR_2$	M	G	M
$MTTR_3$	E	E	G
$MTTR_4$	G	G	G

Table 5.7 Layer-wise Experts' opinion for MTTR

Factors	E1	E2	E3
$MTTF_1$	G	A	G
$MTTF_2$	VG	G	VG
$MTTF_3$	VG	E	VG
$MTTF_4$	G	VG	A

Table 5.8 Layer-wise Experts' opinion for MTTF

Considering the technique applied by Yazdi, M. et al. (2017) for the calculation of the aggregated result (R_{AG}), a similar method has been used, considering the weightage values tabulated in Table 5.4 in exchange for Consensus Coefficient (CC) for evaluating the aggregated value of fuzzy MTTF and fuzzy MTTR. Lastly, the crisp values of MTTF and MTTR have been enumerated using the method used by Ban, A. et. al. (2020). They had demonstrated the crisp values (CV) against the TFN (l, m, u) as:

$$CV = \frac{l+2m+u}{4} \tag{5.5}$$

The λ and μ have been computed on the basis of crisp values of MTTF and MTTR. The λ and μ are reciprocal of MTTF and MTTR, respectively (Samanta et. al., 2001). After getting the values of λ and μ, reliability assessments of each layer have been conducted.

5.2.3 Reliability Assessment of an Individual System

After deducing the values of λ and μ from above mentioned method, the values of reliability have been calculated. The values of λ for all the layers have been considered as constant from the experts' viewpoint. Hence, the reliability (R) of such cases can be represented as:

$$R = e^{-\lambda t} \tag{5.6}$$

where t is the time considered for the Reliability assessment

Based on the formulation, it has been found as an exponential distribution. Hence, the reliability of each layer for different periods has been computed and reflected in the results section.

5.2.4 Entropy-based Markov analysis for consensus output

The concept of information entropy was pioneered by Shannon, who is a useful tool for information and uncertainty of random variables. It is feasible to set up a system model from the viewpoint of uncertainty with information entropy. From the research work done by Kong et. al. (2019), we get an overview regarding entropy calculation of a random variable along with the calculation of mutual information using differential entropy. Based on the literature review, it has been concluded that two types of entropy calculation are required for the said analysis, and this is also concluded in (Zhao et. al., 2016). Those calculations, namely self-entropy and conditional entropy, are given below and discussed Briefly.

i) Self-Entropy: It is defined as the uncertainty of a random variable with respect to its own observation. Suppose $P(x_i)$ is the probability of the x_i variable, which is discrete in nature and values of i vary from 1 to n, then self-entropy, $h_{i|i}(x_i)$ expressed as:

$$h_{i|i}(x_i) = -\sum_{i=1}^{n} P(x_i) log P(x_i) \quad (5.7)$$

Conditional Entropy: It measures the uncertainty of a random variable about the joint observations with another variable, given that the observation of the second variable is unknown. Variable x_i and x_j have probability $P(x_i)$ and $P(x_j)$, respectively. Then conditional entropy $h_{i|j}(x_i,x_j)$ is expressed as:

$$h_{i|j}(x_i, x_j) = -\sum_{i=1}^{n}\sum_{j=1}^{m} P(x_i\, x_j) log P(x_i|x_j) \quad (5.8)$$

Based on the entropy values, a Markov chain can be initiated. A Markov chain is an iterative process for updating the observations of each variable, which consists of several variable states and transition probabilities. Let U^0 be the initial state vector of the initial local observations, and U^k is the state vector at the *k*th iteration, and W is defined as the transition matrix, then according to the Markov analysis, the expression can be written as (Zhao et. al., 2016):

$$U^k = W^k U^0 \quad (5.9)$$

The elements of the said matrix are assigned in the form of w_{ij}, which are non-negative in nature. w_{ij} define as the weight assigned to a variable from state i to state j, such as $\sum_{j=1}^{m} w_{ij} = 1$, where $0 \leq w_{ij} \leq 1$. After several iterations of U^k, the elements are converted into a consensus value, which is the ultimate findings of the analysis. The details relationship between weight and entropy has been defined by Chung et al. (2000) and shown below.

$$w_{ij} \propto \frac{1}{{h_{j|i}}^{\alpha_{ij}}}\text{ ; where i, j = 1to m} \tag{5.10}$$

The value of α_{ij} has a range of 1 to 2. For easier calculation, it has been considered as 1. The equation (5.9) can be presented in a general term as:

$$w_{ij} = \frac{1}{{h_{j|i}}^{\alpha_{ji}} \sum_{k=1}^{m}\left(\frac{1}{h_{k|i}^{\alpha_{ki}}}\right)}\text{; where i, j = 1to m} \tag{5.11}$$

The values of the weight for every state have been evaluated similarly. After constructing the transition matrix, the consensus values of Reliability and availability have been established, and consequently, the system reliability of availability have been evaluated.

5.3 Results and Discussion

To carry out the research work, the values of MTTR and MTTF have been calculated by considering the data given in Tables 5.2 to 5.8. Said values are tabulated in Table 5.9.

Layer	MTTF in Hours		MTTR in Hours	
Physical	MTTF 1	4676.47	MTTR 1	38.97
Network	MTTF 2	5676.47	MTTR 2	41.91
Cloud & Intelligence	MTTF 3	6323.53	MTTR 3	11.76
Terminal	MTTF 4	5029.41	MTTR 4	25.00

Table 5.9 Layer-wise Crisp values of MTTF and MTTR

Based on the said crisp values, layer-wise λ and μ have been evaluated and entered into Table 5.10.

Layer	λ in Failures/Hrs.		μ in Repairs/Hrs.	
Physical	$\lambda 1$	0.0002138	$\mu 1$	0.02566
Network	$\lambda 2$	0.0001762	$\mu 2$	0.02386
Cloud & Intelligence	$\lambda 3$	0.0001581	$\mu 3$	0.085
Terminal	$\lambda 4$	0.0001988	$\mu 4$	0.04

Table 5.10 Layer-wise Values of Failure Rate (λ) and Repair Rate (μ)

From the Fig. 5.3, the states are identified and probabilities of each state are calculated and tabulated in Table 5.11.

States	Probability	percentage
P1	0.977778339	97.777834
P2	0.008148149	0.8148149
P3	0.007219349	0.7219349
P4	0.001819124	0.1819124
P5	0.004860302	0.4860302
P6	6.01612E-05	0.0060161
P7	1.51594E-05	0.0015159
P8	4.05025E-05	0.0040503
P9	1.34314E-05	0.0013431
P10	3.58857E-05	0.0035886
P11	9.04243E-06	0.0009042
P12	1.11928E-07	1.119E-05
P13	2.99047E-07	2.99E-05
P14	6.67641E-08	6.676E-06
P15	7.53535E-08	7.535E-06
P16	5.56367E-10	5.564E-08

Table 5.11 State-wise Probability of the Smart Factory system

From the above table, it can be seen that the steady state availability of the system is 97.7778% and considering Fig. 5.3, the layer-wise availability can be estimated. Suppose Layer 1 is in a failure state at 2, 6, 7, 8, 12, 13, 15 and 16, respectively. Then the total availability of layer 1 ($A_{layer\ 1}$) can be written as:

$$A_{layer\ 1} = \{1 - (P2 + P6 + P7 + P8 + P12 + P13 + P15 + P16)\} \quad (5.12)$$

Availability values of each layer have been evaluated and given in Table 5.12.

$A_{layer\ 1}$	$A_{layer\ 2}$	$A_{layer\ 3}$	$A_{layer\ 4}$
0.991735541	0.992670694	0.998142989	0.995053825

Table 5.12 Layer-wise values of Availability

Considering the layer-wise values of λ, the Reliability calculation of each layer has been computed following equation (5.3) for a time period varying from 1000 Hours to 5000 Hours with an interval of 1000. The said values have been tabulated in Table 5.13.

Reliability $_{Layer}$	Time Periods in Hours					
	1000	2000	3000	4000	5000	$R_{Average}$
$R_{Physical}$	0.80748	0.65202	0.52649	0.42513	0.34328	0.550885
$R_{Network}$	0.83847	0.70304	0.58949	0.49427	0.41443	0.607946
$R_{Cloud\ \&\ Intelligence}$	0.85373	0.72885	0.62224	0.53123	0.45352	0.637919
$R_{Terminal}$	0.81968	0.67189	0.55074	0.45143	0.37003	0.572758

Table 5.13 Layer-wise Reliability for Different Time Periods

The $R_{Average}$ column of Table 5.13 represents the U^0 of reliability, and all the A_{layer} values from Table 5.12 represent the U^0 of Availability. Considering the Entropy-based Markov analysis, the transition matrix for both parameters has been established in M1 and M2, respectively.

$$\begin{bmatrix} 0.1446 & 0.2849 & 0.3005 & 0.2700 \\ 0.2608 & 0.1721 & 0.2987 & 0.2684 \\ 0.2601 & 0.2823 & 0.1900 & 0.2676 \\ 0.2618 & 0.2842 & 0.2998 & 0.1543 \end{bmatrix}$$

M1: Transition Matrix for Reliability Assessment

$$\begin{bmatrix} 0.1206 & 0.1371 & 0.5395 & 0.2029 \\ 0.1216 & 0.1361 & 0.5395 & 0.2029 \\ 0.1216 & 0.1371 & 0.5385 & 0.2029 \\ 0.1216 & 0.1371 & 0.5395 & 0.2019 \end{bmatrix}$$

M2: Transition Matrix for Availability Assessment

After the establishment of the Transition Matrix (W) the iteration process for both parameters has been carried out based on Equation (5.8) with the help of U^0. After six iterations, the $U^k_{Reliability}$ has been found as $[0.5942248\ 0.5942248\ 0.5942248\ 0.5942248]^T$. Thus, the consensus value for Reliability is written as 0.5942248. As all the values are converted into approximately similar values. This process might be useful for reliability calculation at each time step. Similarly, the consensus value of Availability has been found as 0.995989 after two iterations. Due to the series configuration of the system, the system Reliability and Availability have been evaluated as per the series rules of reliability and availability (Shrinath, L. S.,1991), and results are furnished in Table 5.14.

States	System Reliability	System Availability
Before Iteration	0.122366	0.977778
After the final Iteration	0.124682	0.984053

Table 5.14 Final Results of Reliability and Availability

It is clear evidence of the improvement of the Reliability and Availability of the system. This work has already mentioned the relationship between Availability and Reliability. Hence, the optimum values of system reliability may be obtained by maintaining the component (Layer) reliability close to the consensus value. Thus, the availability of the system can be optimised.

Chapter 6

Risk assessment of a smart AIRP using Rough-RIM Methodology

6.1 Introduction

Water is the other identity of life, as it is the most dominant constituent for the survival of any life on Earth. So, a good quality of drinking water is a must for any human being for a healthy life. A detailed guideline of drinking water quality has been published by the World Health Organisation (WHO) (Edition, F. 2011), and it is obeyed by the major countries all over the world, and India is one of them. The drinking water quality of India has been regulated by IS 10500-2012, Bureau of Indian Standards (2012), under the guidelines of WHO. The following standard suggests permissible limits of various substances in drinking water. Among all the substances, Arsenic is one of the major elements that is very harmful to the human body if it exists beyond the permissible limit in the drinking water. The practical quantification limit for arsenic is in the range of 1–10 µg/L for standard drinking water, as recommended by the WHO. Mandal et al. (2002) have provided a comprehensive review of arsenic around the world, discussing its environmental origin, occurrence, episodes, and impact on human health. The study emphasises the matter regarding Arsenic contamination of groundwater and its subsequent health hazard. As this research work has been conducted under the Indian environment, knowledge regarding drinking water quality in Indian is essential. The continuous improvement of the drinking water supply from 2012 to 2018 in rural and urban areas in India has been shown by Aneesh M. R. (2021), and this work is getting a further boost due to the "Jal Jivan Mission" plan, which was launched in 2019 by the Prime Minister of India. Mawari et al. (2022) investigated the human health risk associated with the heavy metals present in the ground and surface water sources, and inquired about the diseases associated with the metals. During this study, it has been found that Arsenic contributes the most health risk from ingestion of water. It was a Maharashtra-based case study. A similar situation of arsenic contamination in groundwater has been observed in West Bengal, where nine districts of the state have been affected by the same (Mandal et al. 2022). Murshidabad is one of the districts that is highly affected due to groundwater Arsenic contamination. The eastern side of the Bhagirathi River is more affected compared to the western side. The contamination caused various life-threatening diseases, as mentioned in the article. Das et al. (2021) have echoed the same matter with the addition of arsenic contamination in irrigational water. The paper has indicated the poor health condition of the local inhabitants due to several reasons, as well as the potential risk of serious cancerous and non-cancerous diseases through contaminated drinking water intake. To cope with such a scenario, the Government has taken some robust steps. One of them is to set up such water treatment plant that is capable of delivering arsenic-free as well as iron-free drinking water for the local people. The Arsenic-Iron removal plant (AIRP) system has been considered as a worthy choice to counter the situation. A brief overview of such a system, along with a schematic diagram, is explained below.

6.1.1. Smart AIRP system

The case study has been adopted from a service sector associated with rural drinking water supply in West Bengal, India, for monitoring and surveillance of water quality parameters to ensure safe drinking water as per the guidelines of the World Health Organisation (WHO). As per IS 10500-2012 latest edition, water containing Arsenic and Iron above the permissible limit is a major threat nowadays. The permissible limits for arsenic and Iron are 0.01 mg/L and 0.3 mg/L, respectively. During the survey, it was found that the groundwater of a large part of West Bengal has been immensely contaminated with Arsenic and Iron. To confront such threats, a water treatment plant with the addition of an Arsenic and Iron removal mechanism has been implemented. Due to its extensive size and complex mechanism, it is a rigorous task to identify the location of the fault that occurred and respond quickly. To overcome this, a SCADA system has been incorporated with the conventional plant and remodelled it to a smart Arsenic and Iron removal plant (AIRP). The block diagram of a smart AIRP has been displayed in Fig. 6.1, along with the direction of water flow.

The contaminated groundwater fed by the submersible pump has been processed in the oxidation vessel by absorption and co-precipitation mechanisms. In this oxidation process, the air compressor has played an important role in oxidising Iron and Arsenic and parallelly, converts them to an insoluble form with the aid of a chemical oxidant (MnO_2). The undissolved ferric form of Iron precipitated on multi-grade sand, pebbles and Gravel filters where coarse and fine media are mixed in a fixed proportion. Such a filter bed arrangement has retained both large and small suspended particles, and the filtered water passes into the arsenic removal vessel through the discharge manifold. In the next vessel, the negatively charged insoluble Arsenic has precipitated in the absorptive granular media, like as activated alumina /Titanium-based/Granular ferric Hydroxide (GFH) media. Then the processed water is filled into the Overhead reservoir (OHR) and supplied to the rural area thereafter. Meanwhile, the effective removal of captured contaminants from both the Arsenic and Iron filter beds has been carried out using a process called backwash to revive their absorption capacity. In this process, pressured water from high-head OHR is fed into both vessels in the reverse direction with the additional help of an air blower. After a certain interval, when the pressure difference in adjacent pressure transmitters around the vessel is greater than 0.5 Bar, the backwash process helps the filter media to be put back into service. The undissolved particle with backwashed water has been accumulated in the sludge chamber and precipitated at the bottom after a certain period. The sludge separated water in the chamber is pushed into the oxidation chamber for further filtering process with the aid of a recirculation pump, and from this viewpoint, it is called a zero-discharge facility.

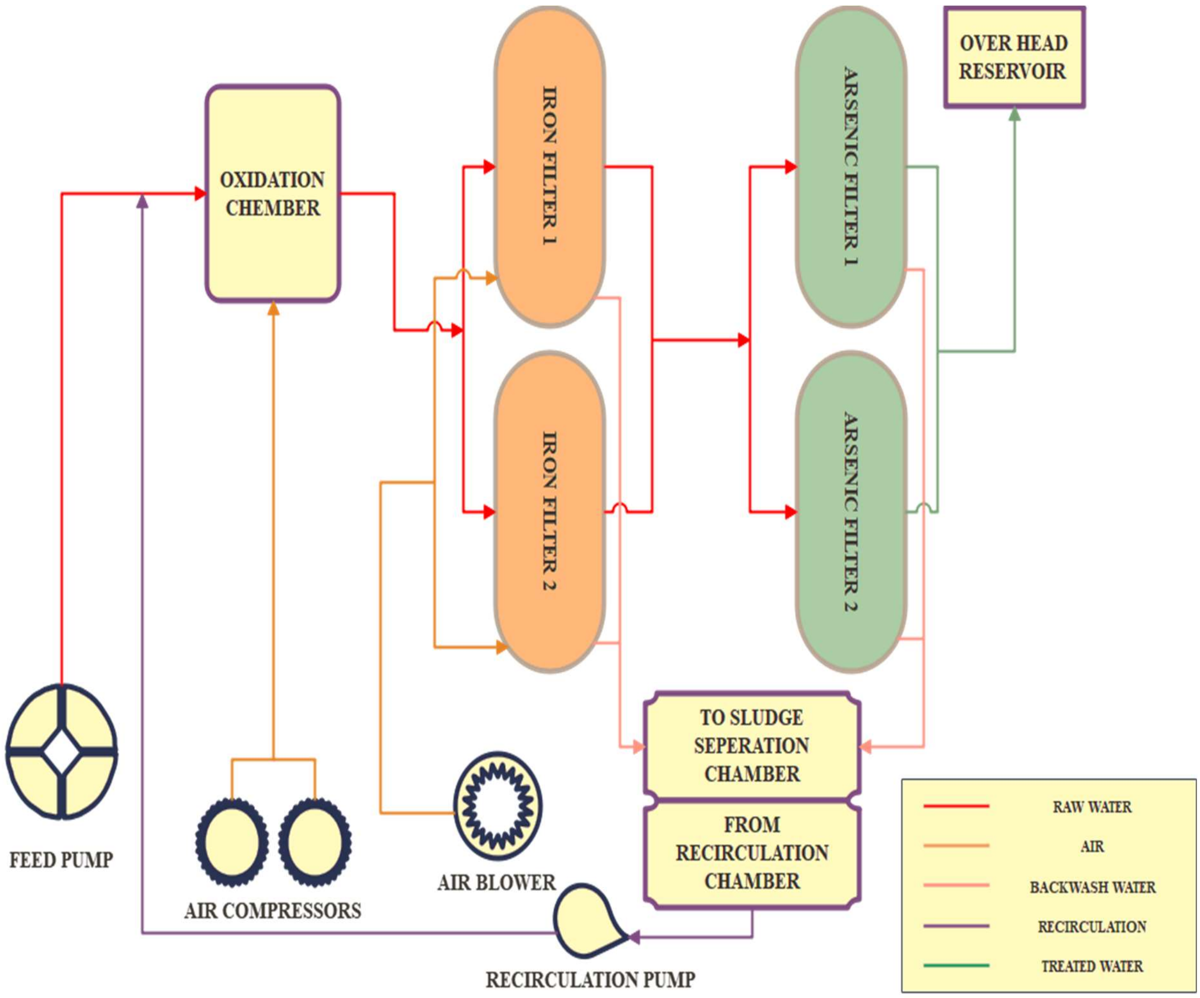

Fig. 6.1 Schematic diagram of an Arsenic-Iron removal plant

Different Remote Terminal Units (RTUs), such as sensors (Flow Meter, Ground Level Sensors, Pressure Transducer, Chlorine Analyzer, etc.) and actuator-operated valves, which are integral parts of the AIRP system, are used to monitor the system's health and transmit necessary data, including Pump on/off, Flow, Chlorine PPM, Overhead Reservoir (OHR) level, and pressures in each filter, from the plant to the local Human-Machine Interface (HMI). This data transmission occurs through various PLCs and multi-function meters via Ethernet or Application Programming Interface (API) signals. The process of transmitting and remotely supervising real-time data from RTUs to the HMI is known as a SCADA-controlled system. A pictorial representation of data transmission in a Smart AIRP system is shown in Fig. 6.2.

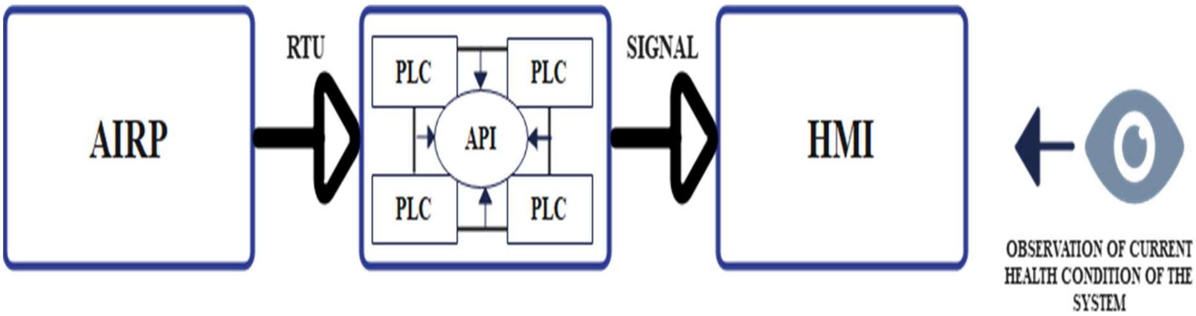

Fig. 6.2 Data transfer methodology of a Smart AIRP system

To operate such a system smoothly, the operating staff associated with the system must maintain it to counter any failures. That's why the failures associated with the system must be known. To do so, three experts, namely E1, E2, and E3, have been appointed to identify potential failures in the system that could directly affect people's health due to the consumption of water from the system. The experts have identified the potential failures along with their prime causes, effects and their mode of detection as tabulated in Table 6.1. But, due to some restrictions, the identity of the experts has not been disclosed.

No.	Failure Mode	Prime Cause	Effects	Detection
F1	Electro-Mech Equipment failure at the pump House	1. Motor Burning 2. Panel or VS Damage 3. Electrical Cable Fault	1. Water Supply Suspended From sources	1. No reading at the inlet flow meter and inlet pr. transmitter
F2	Compressor Malfunction	1. Compressor jam due to lubricant oil slugging 2. Power relay damage	1. Oxidation of contaminated water will not be completed, and iron and Arsenic will not be filtered properly as this will not be insoluble form.	1. Water test result 2. Reading from the pressure transmitter at the outlet of the compressor
F3	No filtration at the iron removal filter	1. Actuator valve failure 2. Low absorption capacity of the filter medium	1. Further movement of water from the iron chamber becomes restricted.	1. Increased pr difference between adjacent pr. Transmitter 2. Water test report.

No.	Failure Mode	Prime Cause	Effects	Detection
F4	No filtration at the Arsenic removal filter	1. Actuator valve failure 2. Low absorption capacity of GEH filter medium	1. Exceeding the permissible limit of arsenic can cause various fatal diseases.	1. Increased pr difference between adjacent pr. Transmitter 2. Water test result from the lab.
F5	Improper backwash operation	1. Malfunction of the blower 2. Backwash actuator valve damages.	1. The service life of both filter media has decreased.	1. Increased pr difference between adjacent pr. Transmitter 2. Water test report from the Lab.
F6	Malfunction of the Automatic plunger-type chlorinator	1. Chlorinator suction Ball valve jammed due to a chlorine granule 2. Jam of chlorine dosing pipeline, valve and socket	1. Health hazard due to bacterial contamination	1. Lab Test 2. Field Test Kit
F7	Failure of the Recirculation pump	1. Motor Burning 2. Water level sensor failure 3. Pump Bearing Jam	1. Non-availability of a discharge facility 2. The backlash process gets interrupted	1. Level sensor in the sludge chamber.
F8	SCADA control system failure	1. Ethernet and Module failure 2. PLC failure 3. RTU failure	1. Improper Supervision and Monitoring 2. Sensor and Actuator Malfunction, and as a consequence filtration process is interrupted	1. Non-functional HMI (Human Machine Interface) 2. Water Test Result 3. Alarm Indication

Table 6.1 Types of failure associated with a Smart AIRP, along with cause, effect, & Detection

To overcome any kind of mishap during operation, the Failure Mode and Effects Analysis (FMEA) tool has been utilised in this research work for risk assessment of the failures. The FMEA is a worthy tool that is used to look at the ways through which a system can fail and prevent the same before actual failure occurs. It provides necessary quantitative or qualitative measures to guide the implementation of corrective actions by focusing on the main failure modes and their impact on the system. Traditionally, using the data and knowledge of the system as provided by the experts, each potential failure mode **(i.e. Failures)** and effect is rated based on three factors, e.g. Severity (S), Occurrence (O) and Detection (D) on a 10-point scale from low to high. S indicates the criticality of the failure effect, while O is the indicator of frequency of failure, and D is the index through which one can identify the quickness of detection of the failures. A Risk Priority Number (RPN) of each failure mode will be generated after multiplying all the factors and ranked according to the values of RPN in a descending order, i.e. the failure mode having the highest RPN will get the first rank, and instant corrective action has to be taken for the said failure mode (Mikulak et al. 2017). This process is beneficial for a single opinion. For multiple opinions as well as the vagueness of data, this task will be more complicated than the RPN calculation. Apart from that, for any modification or advancement of the traditional FMEA tool, the RPN assessment is not sufficient (Wan et al. 2019). To deal with such difficulties, the concept of Rough Set Theory and Multi-Criteria Decision Making (MCDM) techniques has been incorporated with the traditional FMEA model for better outcomes. The rough set theory has portrayed a key role for both the weightage assessment of the criteria, as well as in computing the ranking of the alternatives, i.e. failure mode in this case. The Rough Set Theory has the unique ability to manage uncertainty without additional information, such as a membership function (Fuzzy Set) (Zadeh, L. A. 1965), any probability distribution (Statistics), or a basic probability assignment (Dempster-Shafer theory) (Shafer, G. 1992). A brief overview of Rough Set theory has been discussed below.

6.1.2 Rough Set Theory

The basic knowledge of rough set theory was proposed by Pawlak (1982). The theory was inspired by an outstanding comment of Harold Pinter, as quoted: "Apart from the known and the unknown, what else is there?". Considering the intermediate space between known and unknown, the pillar of the concept has been set up. It is a mathematical tool for imperfect data analysis. This philosophy is founded on the assumption regarding the universe of discourse of an object and its associated information. The objects that are characterised by similar facts are indiscernible in view of the obtainable information about them. The methodology of generating the indiscernibility relation is the mathematical basis of rough set theory. Any set of all undefinable similar objects is known as an elementary set and forms a molecular space of knowledge about the universe. Any union of some elementary sets is referred to as a crisp set; otherwise, it is called a rough set. A rough set cannot be characterised in terms of information about its elements as compared to precise sets. A rough set is an accumulation of two precise sets, commonly known as the Lower Approximation and Upper Approximation. The lower approximation assures all objects belong to the set, and the upper approximation implies the possibility that all objects belong to the set. The boundary region of the rough set is defined as the difference between the upper and lower approximations. This is to understand that the approximations are the elementary concepts of the rough set theory. The fig. shows the fundamental concept of the rough set theory. Let us assume X be a certain subset of the universe (U), then a pictorial representation of the concept of rough set can be understood from Fig. 6.3. Now, let us assume that there are set of n classes, where R = (c_1, c_2......c_n) in the universe and for any class $c_i \in R$ where $1 \leq i \leq n$ then, according to Das et al. (2024), the basic formulas of rough set theory have been briefly discussed. Firstly, the lower approximation of c_i has been expressed as:

$$\underline{Apr(c_i)} = U\{X \in U/R(X) \leq c_i\} \quad (6.1)$$

Similarly, the upper approximation of the c_i has been shown below:

$$\overline{Apr(c_i)} = U\{X \in U/R(X) \geq c_i\} \quad (6.2)$$

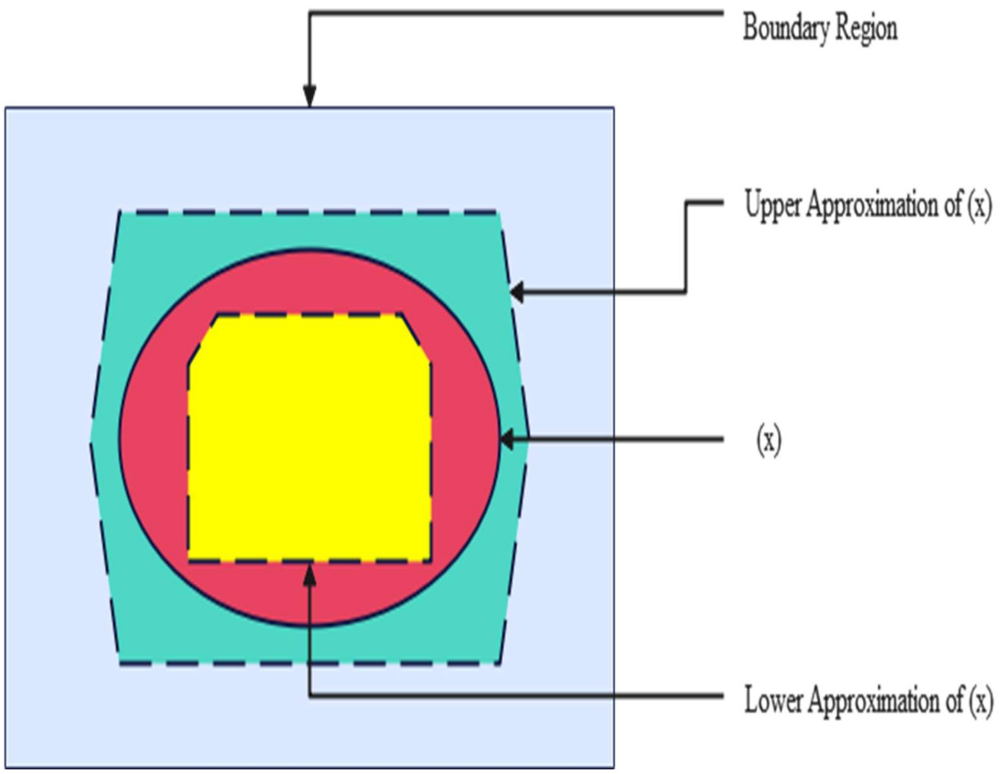

Fig. 6.3 Pictorial Representation of Rough Set

Hence, the boundary region of c_i has been represented as:

$$Bnd(c_i) = U\{X \in U/R(X) \neq c_i\};$$

$$= \{X \in U/R(X) > c_i\} \cup \{X \in U/R(X) < c_i\} \quad (6.3)$$

Based on the above equations, the class c_i can be represented by a rough number (RN), where it can be defined using its lower limit $\{\underline{Limit}(c_i)\}$ and upper limit $\{\overline{Limit}(c_i)\}$, which are written below:

$$\{\underline{Limit}(c_i)\} = \frac{1}{M_L}\sum R(X)|X \in \underline{Apr}(c_i) \quad (6.4)$$

$$\{\overline{Limit}(c_i)\} = \frac{1}{M_C}\sum R(X)|X \in \overline{Apr}(c_i) \quad (6.5)$$

Where M_L and M_C are the number of objects observed in the lower approximation and upper approximation, respectively. Based on the values, the rough boundary intervals of the c_i have been observed as:

$$RBnd_{c_i} = \{\overline{Limit}(c_i) - \underline{Limit}(c_i)\} \quad (6.6)$$

Likewise, the vague class c_i in terms of a rough number has been represented as:

$$RN(c_i) = [\{\underline{Limit}(c_i)\}, \{\overline{Limit}(c_i)\}] \quad (6.7)$$

Considering all the potentiality, the rough set theory has been integrated with a weight assessment method for the calculation of the weightage of the criteria, as well as combined with an MCDM method for ranking assessment of the failure mode. The framework of the research work has been developed and discussed in the Research Methodology section with the help of a flow chart. The concept of the R-SWARA and R-RIM has been discussed herewith. The next section emphasises the past works regarding FMEA, Rough set theory, MCDM, sensitivity analysis, and their combined essence towards the current case study has been derived.

6.2 Research Methodology

The major aspect of this research work is to identify the prime failures of the said systems based on their severity and rank them accordingly. To do so, a proper methodology is essential, along with the necessary mathematical tools. Hence, a methodological structure of the work has been portrayed below.

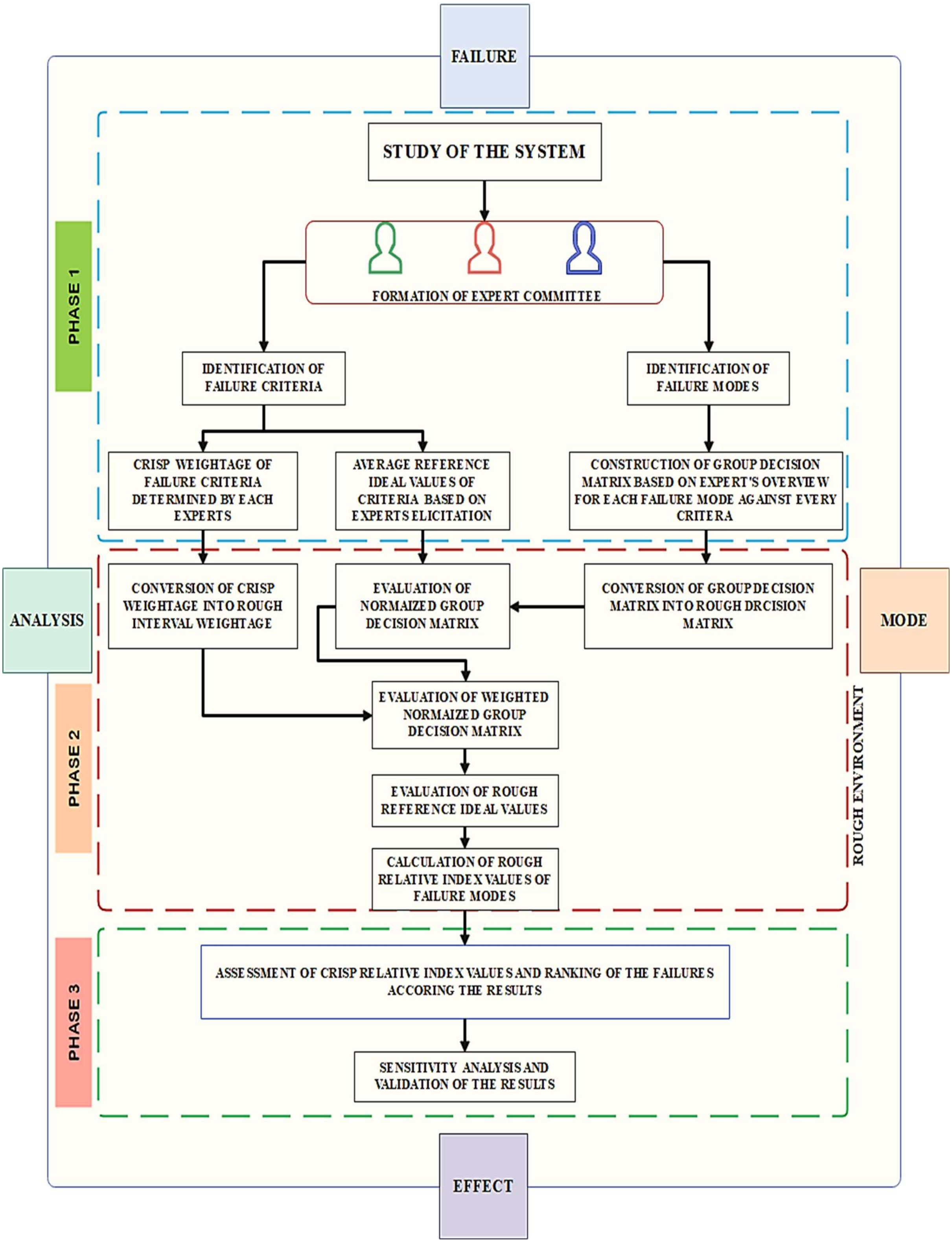

Fig. 6.4 Methodological structure of the research work

A proper weightage of each criterion has been assigned for an optimal result. The experts from the respective fields, as mentioned before, have provided their individual opinions for each criterion on the basis of a 10-point scale. Based on the opinions, the weightage of each criterion has been evaluated using the R-SWARA method. The detailed method is explained below.

6.2.1 Weightage assessment of criteria using R-SWARA

The primary concept of the R-SWARA method was introduced by Zavadskas et al. (2018), as already stated. It has been found as an effective tool while computing the weightage of the criterion, and the methodology of the same has been re-portrayed, mentioning the steps associated with the method.

Step 1: Identification of the criterion associated with the FMEA process, where five criteria, namely Severity (C1), Occurrence (C2), Detection (C3), Environmental Effect (C4) and cost factor (C5) have been considered for the failure analysis of the system in this study, as said before.

Step 2: Rating of the criterion based on experts' elicitation, where the experts have chosen a 10-point scale for facilitation of the ratings. In accordance with the scale, lower values of rating indicate higher significance and vice versa. The criterion has been arranged in a most essential to least essential order for proper adaptation of the R-SWARA method.

Step 3: Conversion of the expert's response into a group rough Matrix, $R(C_N)$, following equations (6.4) to (6.7), where the value of N has been referred to as the particular criteria. The $R(C_N)$ has been described as:

$$R(C_N) = [C_N^L, C_N^U] \quad (6.8)$$

The terms "max (C_r^U)" and "max (C_r^L)" are defined as the Highest value of upper approximation and lower approximation in the group rough matrix.

Step 4: Normalization of rough Matrix, $R(S_N) = [S_N^L, S_N^U]$ where the first element, i.e. the most important criterion (N=1) has been assigned as [1.00,1.00]. Normalization of rough Matrix, $R(S_X)$, for the remaining criterion, i.e. for N > 1, has been described below.

$$R(S_N) = \left[S_N^L = \frac{C_N^L}{\max(C_r^U)}, S_N^U = \frac{C_N^U}{\max(C_r^L)}\right] \quad (6.9)$$

Where N = 2,3…m, where m is equal to 5 for this problem, and the ultimate number of criteria, and the first element of the criteria, i.e. N=1, has been excluded as per the R-SWARA methodology.

Step 5: Construction of matrix R(K_N) = $[K_N^L, K_N^U]$, where the values of matrix R(S_N) have been used for calculation.

$$\left.\begin{array}{ll} R(K_N) = [1.00,1.00] & for\ N = 1 \\ R(K_N) = [S_N^L + 1, S_N^L + 1] & for\ N = 2,3 \ldots .m \end{array}\right\} \quad (6.10)$$

Step 6: Evaluation of matrix with recalculated weights, R(Q_N) = $[Q_N^L, Q_N^U]$, which has been described below.

$$R(Q_N) = \left[Q_N^L = \begin{cases} 1.00\ for\ N = 1 \\ \frac{Q_{N-1}^L}{K_N^U}\ for\ N > 1 \end{cases}, Q_N^U = \begin{cases} 1.00\ for\ N = 1 \\ \frac{Q_{N-1}^U}{K_N^L}\ for\ N > 1 \end{cases} \right] \quad (6.11)$$

Step 7: Computation of relative weightage, R(W_N) = $[W_N^L, W_N^U]$, as given below.

$$[W_N^L, W_N^U] = \left[\frac{[Q_N^L, Q_N^U]}{\sum_{N=1}^{m}[Q_N^L, Q_N^U]} \right] \quad (6.12)$$

Step 8: Normalisation of the weightage using the following equation (Das et. al. 2024).

$$w_N = [w_N^L, w_N^U] = \left[\frac{W_N^L}{Max(W_N^U)}, \frac{W_N^U}{Max(W_N^U)} \right] \quad (6.13)$$

After the evaluation of the weightage, it has been utilised in the R-RIM for ranking assessment of the failures associated with the Smart AIRP system. Hence, a holistic overview of the R-RIM is explained below.

6.2.2 Ranking assessment of the failures using the R-RIM technique

To carry out any MCDM problem, the fundamental steps of the said technique have to be known. Generally, two prime constituents of any MCDM are the criteria and Alternatives for final assessment. The R-RIM is an upgrade of RIM, and unlike other MCDM methods, it requires Reference ideal values for all the criteria. Considering the motive of the study, the methodology of the R-RIM technique has been discussed with all the necessary steps.

Step 1: Thorough study of the respective domain and bring out the essential criteria. In this research work, the domain and the criteria have already been discussed before, and the said criteria have been implemented in R-RIM for subsequent assessment.

Step 2: Identification of alternatives, which are the prime auditable entities through MCDM methods. Under this study, different types of failures associated with the Smart AIRP system have been considered as the alternatives and the details of the same have been portrayed in Table 6.1.

Step 3: Construction of a decision matrix based on the Elicitation of the expert regarding the importance of the failures to make the system stable as well as reliable. Individual ratings have been given by each expert against each criterion, and the 10-point scale has been adopted for the rating, where higher values indicate higher importance. The matrix P represent a typical decision matrix as follows:

$$P = \begin{bmatrix} y_{1S}^n & y_{1O}^n & y_{1D}^n & y_{1E}^n & y_{1C}^n \\ y_{2S}^n & y_{2O}^n & y_{2D}^n & y_{2E}^n & y_{2C}^n \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{iS}^n & y_{iO}^n & y_{iD}^n & y_{iE}^n & y_{iC}^n \end{bmatrix} \tag{6.14}$$

Where n represents the number of experts (1, 2..., n) and "i" indicates the failure modes, which range from 1 to I, with I being 8 in this case study. The five columns represent the criteria (N): S for Severity, O for Occurrence, D for Detection, E for Environmental Effect, and C for Cost factor.

Step 4: Reckon with the Reference ideal values as well as the limiting values of each criterion to carry out the RIM technique, where an average rating of experts has been considered as the final values of reference ideals. A 10-point scale has been considered for the rating process.

Step 5: Normalization of the values that have been received based on experts' elicitation, based on the range and reference ideal values. To carry out the normalization procedure, the research work of Das et.al. (2023) has been considered, and the necessary numerical calculation has been provided in equation (6.15). A and B represent the lower and the higher values of reference ideals, respectively. On the other hand, C and D indicate the lower and higher limit, respectively, i.e. the range of the criteria. The elements of the decision matrix have been assigned by y as shown in equation 6.14.

$$f(y,[A,B],[C,D]) = \begin{bmatrix} 1 & When, y \in [C,D] \\ 1 - \frac{dmin(y,[C,D])}{|A-C|} & When, y \in [A,C] \; and \; A \neq C \\ 1 - \frac{dmin(y,[C,D])}{|D-B|} & When, y \in [D,B] and \; D \neq B \end{bmatrix} \tag{6.15}$$

Step 6: Construction of the group rough matrix based on the normalized value (Denoted by Y) obtained from the previous step for each alternative against each criterion. Equations (6.4) and (6.5) have been utilized to pursue the same. The lower approximation of the group rough matrix has been denoted as Y_{iN}^L, and the upper approximation has been denoted as Y_{iN}^U.

$$Y_{iN}^L = \frac{1}{M_L} \sum R(Z) | Z \in \underline{Apr}(Y) \tag{6.16}$$

$$Y_{iN}^U = \frac{1}{M_C} \sum R(Z) | Z \in \overline{Apr}(Y) \tag{6.17}$$

Where Z is the respective normalized observations of a failure mode against each criterion, and on the other side, M_L and M_C are the number of objects observed in the lower and upper approximation, respectively.

Step 7: Rough normalization of the group rough matrix, using the following equations.

$$Y_{iN}^{L'} = \frac{Y_{iN}^{L}}{Max_{i=1}^{I}\{Max[Y_{iN}^{L}, Y_{iN}^{U}]\}} \tag{6.18}$$

$$Y_{iN}^{U'} = \frac{Y_{ir}^{U}}{Max_{i=1}^{I}\{Max[Y_{iN}^{L}, Y_{iN}^{U}]\}} \tag{6.19}$$

Where $[Y_{iN}^{L'}, Y_{iN}^{U'}]$, defined as the normalized limit of a rough interval $[Y_{iN}^{L}, Y_{iN}^{U}]$ and makes a range of rough numbers between the interval 0 and 1.

Step 8: Calculation of the weighted normalized matrix, for which both normalized weightage values of the criterion and rough normalizations of alternatives are essential. To carry out the calculation, the normalized weightage of the criterion has been revealed using equation (6.13), and the evaluation of rough normalization of alternatives has already been discussed in the previous step. Combining both of them using equations (6.20) and (6.21), the weighted normalized values for upper approximations and lower approximations have been computed.

$$z_{iN}^{L} = Y_{iN}^{L'} * w_{N}^{L} \tag{6.20}$$

$$z_{iN}^{U} = Y_{iN}^{U'} * w_{N}^{U} \tag{6.21}$$

Step 9: Calculation of Positive reference ideal (I_i^+) and Negative reference ideal (I_i^-) values for both lower approximation (I_i^{L-}, I_i^{L+}) and upper approximation (I_i^{U-}, I_i^{U+}), and this step could be considered as the backbone of the R-RIM methodology.

$$I_i^{L+} = \sqrt{\sum_{j=1}^{N}(z_{iN}^{L} - w_{N}^{L})^2} \tag{6.22}$$

$$I_i^{L-} = \sqrt{\sum_{j=1}^{N}(z_{iN}^{L})^2} \tag{6.23}$$

$$I_i^{U+} = \sqrt{\sum_{j=1}^{N}(z_{iN}^{U} - w_{N}^{U})^2} \tag{6.24}$$

$$I_i^{U-} = \sqrt{\sum_{j=1}^{N}(z_{iN}^{U})^2} \tag{6.25}$$

Based on the above equations, the relative index values have been assessed.

Step 10: Computation of Relative index values for both lower (R_i^L) and upper (R_i^U) approximations, respectively, using Reference ideal values

$$R_i^L = \frac{I_i^{L-}}{I_i^{L+} + I_i^{L-}} \tag{6.26}$$

$$R_i^U = \frac{I_i^{U-}}{I_i^{U+} + I_i^{U-}} \tag{6.27}$$

Step 11: For each alternative, there are two Relative index values, i.e. R_i^L and R_i^U have been generated. To obtain the crisp value of R_i, the method applied by Shojaei et al. (2020) for the conversion of a rough set into a crisp set has been adopted. A simple average method has been used by them for the crisp value assessment.

$$R_i = \frac{(R_i^L + R_i^U)}{2} \tag{6.28}$$

Step 12: Ranking of alternatives based on the crisp value of R_i. It should be noted that the minimum value of R_i most hazardous failure according to the problem definition. Hence, considering the effect of the failures, first rank has been granted to the alternative corresponding to the lowest R_i value and rank thereafter according to severity, i.e. next minimum R_i value and so on.

6.3 Results and Findings

This section has started from the construction of a table, which shows the criteria-wise score assigned by the three experts.

Criterion	**Experts**		
	E1	**E2**	**E3**
S	2	4	2
D	3	3	4
E	4	5	4
O	5	4	5
C	4	6	7

Table 6.2 Criteria-wise score assigned by the Experts

Based on the values, the Group Rough matrix has been developed using Equations (6.4) to (6.7), and the results are tabulated below.

Criteria	Group Rough Matrix	
	Lower Approximation of the score	Upper Approximation of the score
S	2.222	3.111
D	3.111	3.556
E	4.111	4.556
O	4.444	4.889
C	4.889	6.389

Table 6.3 Criteria-oriented group Rough Matrix

Considering the result, the R-SWARA approach has been adopted for weightage assessment of the criteria. Hence, the result is shown below.

Criteria	Lower Approximation of Weightage (W_N^L)	Upper Approximation of Weightage (W_N^U)
S	0.406545	0.477683
D	0.235368	0.321249
E	0.121838	0.195469
O	0.060919	0.115276
C	0.026408	0.065304

Table 6.4 Rough weightage of each criterion

Based on the rough weightage values of the alternatives, the Normalised Rough weightage has been evaluated using Equation (6.13).

Criteria	Lower Approximation of Normalized Weightage (w_N^L)	Upper Approximation of Normalized Weightage (w_N^U)
S	0.851078	1
D	0.492729	0.6725146
E	0.25506	0.409202
O	0.12753	0.2413243
C	0.055284	0.1367108

Table 6.5 Normalized rough weightage of each criterion

Alternatively, a decision matrix has been formed, where each expert has presented the assessment score of each failure mode against each alternative using a 10-point scale, and the results are tabulated below.

Failure Mode No.	Criteria														
	S			O			D			E			C		
	E1	E2	E3	E1	E2	E3	E1	E2	E3	E1	E2	E3	E1	E2	E3
F1	9	8	9	7	6	7	6	5	6	9	10	9	6	4	5
F2	8	10	9	3	2	2	4	4	5	9	8	7	7	5	6
F3	6	5	7	4	3	2	4	3	2	3	3	2	4	5	5
F4	9	8	9	5	4	6	5	5	6	9	9	10	7	8	7
F5	7	9	7	6	8	7	8	9	8	7	9	7	5	4	3
F6	9	9	10	6	5	3	5	6	3	8	7	7	3	2	3
F7	6	5	8	3	5	2	6	4	6	8	7	8	4	4	5
F8	8	7	8	8	9	7	5	5	6	7	9	6	9	10	9

Table 6.6 Decision Matrix of the failure modes and their assigned score assigned by Experts

The Range and Reference ideal values for each criterion have been provided by the experts. Considering the 10-point scale, the range of all criteria has been treated as the same, although the reference ideal values differ among experts. Therefore, the average values from all experts' inputs have been adopted as the final Reference ideal values for each criterion. The range and reference ideal values for each criterion are listed below in a tabulated format.

Criteria	Range of Criteria	Reference Ideal			Avg. Reference Ideal
		E1	E2	E3	
S	1-10	6-8	7-8	6-7	6.33 - 7.67
O	1-10	6-7	6-7	6-7	6 - 7
D	1-10	5-8	5-7	6-7	5.33 - 7.33
E	1-10	4-7	4-7	4-6	4 - 6.67
C	1-10	6-7	7-8	6-7	6.33 - 7.33

Table 6.7 Range and Reference ideal values of the criteria

Considering Table 6.6, 6.7, and Equation (6.15), the normalization process has been carried out, and the said matrix has been displayed in the table below.

Failure	S			O			D			E			C		
Mode No.	**E1**	**E2**	**E3**	**E1**	**E2**	**E3**	**E1**	**E2**	**E3**	**E1**	**E2**	**E3**	**E1**	**E2**	**E3**
F1	0.4292	0.8584	0.4292	1.0000	0.8000	1.0000	1.0000	0.9238	1.0000	0.3003	0.0000	0.3003	0.9381	0.5629	0.7505
F2	0.8584	0.0000	0.4292	0.4000	0.2000	0.2000	0.6928	0.6928	0.9238	0.3003	0.6006	0.9009	1.0000	0.7505	0.9381
F3	0.9381	0.7505	1.0000	0.6000	0.4000	0.2000	0.6928	0.4619	0.2309	0.6667	0.6667	0.3333	0.5629	0.7505	0.7505
F4	0.4292	0.8584	0.4292	0.8000	0.6000	1.0000	0.9238	0.9238	1.0000	0.3003	0.3003	0.0000	1.0000	0.7491	1.0000
F5	1.0000	0.4292	1.0000	1.0000	0.6667	1.0000	0.7491	0.3745	0.7491	0.9009	0.3003	0.9009	0.7505	0.5629	0.3752
F6	0.4292	0.4292	0.0000	1.0000	0.8000	0.4000	0.9238	1.0000	0.4619	0.6006	0.9009	0.9009	0.3752	0.1876	0.3752
F7	0.9381	0.7505	0.8584	0.4000	0.8000	0.2000	1.0000	0.6928	1.0000	0.6006	0.9009	0.6006	0.5629	0.5629	0.7505
F8	0.8584	1.0000	0.8584	0.6667	0.3333	1.0000	0.9238	0.9238	1.0000	0.9009	0.3003	1.0000	0.3745	0.0000	0.3745

Table 6.8 Failure Modes-wise Normalized Decision Matrix

Based on the result displayed in Table 6.8, the group rough matrix has been generated using equations (6.16) and (6.17), and the same result has been tabulated below.

Failure Mode No.	S		O		D		E		C	
	Y_{iS}^{L}	Y_{iS}^{U}	Y_{iO}^{L}	Y_{iO}^{U}	Y_{iD}^{L}	Y_{iD}^{U}	Y_{iE}^{L}	Y_{iE}^{U}	Y_{iC}^{L}	Y_{iC}^{U}
F1	0.4769	0.6676	0.8889	0.9778	0.9577	0.9915	0.1335	0.2669	0.6567	0.8443
F2	0.2146	0.6438	0.2222	0.3111	0.7185	0.8211	0.4505	0.7508	0.8303	0.9551
F3	0.8303	0.9551	0.3000	0.5000	0.3464	0.5774	0.4815	0.6296	0.6462	0.7296
F4	0.4769	0.6676	0.7000	0.9000	0.9323	0.9661	0.1335	0.2669	0.8606	0.9721
F5	0.6829	0.9366	0.8148	0.9630	0.5410	0.7074	0.5672	0.8342	0.4690	0.6567
F6	0.1907	0.3815	0.5778	0.8778	0.6500	0.9190	0.7341	0.8675	0.2710	0.3544
F7	0.8013	0.8951	0.3222	0.6222	0.8294	0.9659	0.6340	0.7674	0.5837	0.6671
F8	0.8741	0.9371	0.5000	0.8333	0.9323	0.9661	0.5449	0.8947	0.1665	0.3329

Table 6.9 Failure Modes-wise group rough Matrix

Alike Table 6.5, the rough normalization of the group rough matrix with respect to each criterion has been calculated using equations (6.18) and (6.19).

Failure Mode No.	S		O		D		E		C	
	$Y_{iS}^{L'}$	$Y_{iS}^{U'}$	$Y_{iO}^{L'}$	$Y_{iO}^{U'}$	$Y_{iD}^{L'}$	$Y_{iD}^{U'}$	$Y_{iE}^{L'}$	$Y_{iE}^{U'}$	$Y_{iC}^{L'}$	$Y_{iC}^{U'}$
F1	0.4993	0.6990	0.9091	1.0000	0.9658	1.0000	0.1492	0.2983	0.6755	0.8685
F2	0.2247	0.6741	0.2273	0.3182	0.7246	0.8282	0.5034	0.8391	0.8541	0.9825
F3	0.8694	1.0000	0.3068	0.5114	0.3494	0.5823	0.5381	0.7037	0.6648	0.7505
F4	0.4993	0.6990	0.7159	0.9205	0.9402	0.9744	0.1492	0.2983	0.8853	1.0000
F5	0.7150	0.9806	0.8333	0.9848	0.5456	0.7135	0.6340	0.9323	0.4825	0.6755
F6	0.1997	0.3994	0.5909	0.8977	0.6555	0.9269	0.8204	0.9696	0.2788	0.3646
F7	0.8390	0.9372	0.3295	0.6364	0.8364	0.9741	0.7086	0.8577	0.6004	0.6862
F8	0.9152	0.9811	0.5114	0.8523	0.9402	0.9744	0.6090	1.0000	0.1712	0.3425

Table 6.10 Normalized Failure Modes-wise group rough Matrix

Now, both the Normalized Failure Modes-wise group rough Matrix of each failure mode as well as the Normalized rough weightage of each criterion have been assessed, and based on those results, the weighted normalized group decision matrix has been developed using equations (6.20) and (6.21) and described in Table 6.11.

Failure Mode No.	S		O		D		E		C	
	z_{iS}^{L}	z_{iS}^{U}	z_{iO}^{L}	z_{iO}^{U}	z_{iD}^{L}	z_{iD}^{U}	z_{iE}^{L}	z_{iE}^{U}	z_{iC}^{L}	z_{iC}^{U}
F1	0.4249	0.6990	0.1159	0.2413	0.4759	0.6725	0.0380	0.1221	0.0373	0.1187
F2	0.1912	0.6741	0.0290	0.0768	0.3571	0.5569	0.1284	0.3434	0.0472	0.1343
F3	0.7399	1.0000	0.0391	0.1234	0.1721	0.3916	0.1373	0.2880	0.0368	0.1026
F4	0.4249	0.6990	0.0913	0.2221	0.4633	0.6553	0.0380	0.1221	0.0489	0.1367
F5	0.6085	0.9806	0.1063	0.2377	0.2688	0.4798	0.1617	0.3815	0.0267	0.0923
F6	0.1700	0.3994	0.0754	0.2166	0.3230	0.6233	0.2093	0.3968	0.0154	0.0498
F7	0.7140	0.9372	0.0420	0.1536	0.4121	0.6551	0.1807	0.3510	0.0332	0.0938
F8	0.7789	0.9811	0.0652	0.2057	0.4633	0.6553	0.1553	0.4092	0.0095	0.0468

Table 6.11 Weighted Normalized Failure Modes-wise group rough Matrix

After the evaluation of the Weighted Normalized Failure Modes-wise group rough Matrix, the next step associated with the R-RIM is to calculate the Positive reference ideal (I_i^{+}) and Negative reference ideal (I_i^{-}) for both lower Approximation (I_i^{L+}, I_i^{L-}) and upper approximation (I_i^{U+}, I_i^{U-}) using equations (6.22) to (6.25). All the respective values have been tabulated below.

Failure Mode No.	I_i^{L+}	I_i^{U+}	I_i^{L-}	I_i^{U-}
F1	0.478981	0.416351	0.650646	1.013976
F2	0.692554	0.388598	0.428498	0.952037
F3	0.370363	0.329664	0.773825	1.123402
F4	0.480525	0.416762	0.638262	1.000483
F5	0.344887	0.200624	0.693344	1.184244
F6	0.70648	0.609425	0.427703	0.868882
F7	0.196469	0.131062	0.845715	1.209581
F8	0.148333	0.100023	0.921854	1.266472

Table 6.12 Calculated Reference Ideal values

Based on the values as stated above, the Relative index for the lower approximation (R_i^{L}) and upper approximation (R_i^{U}) have been enumerated. The simple average of R_i^{L} and R_i^{U} has been done for the final assessment of crisp Relative index values (R_i), which has been used for the final ranking assessment of the Failure Modes using equation (6.28). The said values have been tabulated below.

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Failure Mode No.	R_i^L	R_i^U	R_i	Rank
F1	0.57598	0.70891	0.64245	4
F2	0.38223	0.71014	0.54618	2
F3	0.67631	0.77313	0.72472	5
F4	0.57049	0.70594	0.63821	3
F5	0.66781	0.85513	0.76147	6
F6	0.37710	0.58775	0.48243	1
F7	0.81148	0.90224	0.85686	7
F8	0.86140	0.92680	0.89410	8

Table 6.13 Relative Index values and respective Ranking of the failure modes

A comparative analysis has been performed, comparing the R-RIM results with other Rough Set-based FMEA methods and the traditional FMEA approach. The ranking comparisons for all methods are summarised in Table 6.14 and illustrated in Fig. 6.5.

Failure Mode No.	R-TOPSIS		R-MABAC		Traditional FMEA		R-RIM	
	Closeness Coefficient	Rank	Final Score	RANK	Average RPN	Rank	Crisp Relative Index	Rank
F1	0.3557	2	-0.734	1	611.1605	2	0.6424	4
F2	0.4024	5	-0.036	5	121.3333	7	0.5462	2
F3	0.6250	8	1.093	8	30.85714	8	0.7247	5
F4	0.3737	3	-0.261	4	294.1414	4	0.6382	3
F5	0.3447	1	-0.686	2	857.1759	1	0.7615	6
F6	0.3868	4	-0.575	3	558.963	3	0.4824	1
F7	0.4967	7	0.294	7	199.2023	6	0.8569	7
F8	0.4270	6	0.002	6	257.0159	5	0.8941	8

Table 6.14 Comparative analysis of the Failure mode Ranking

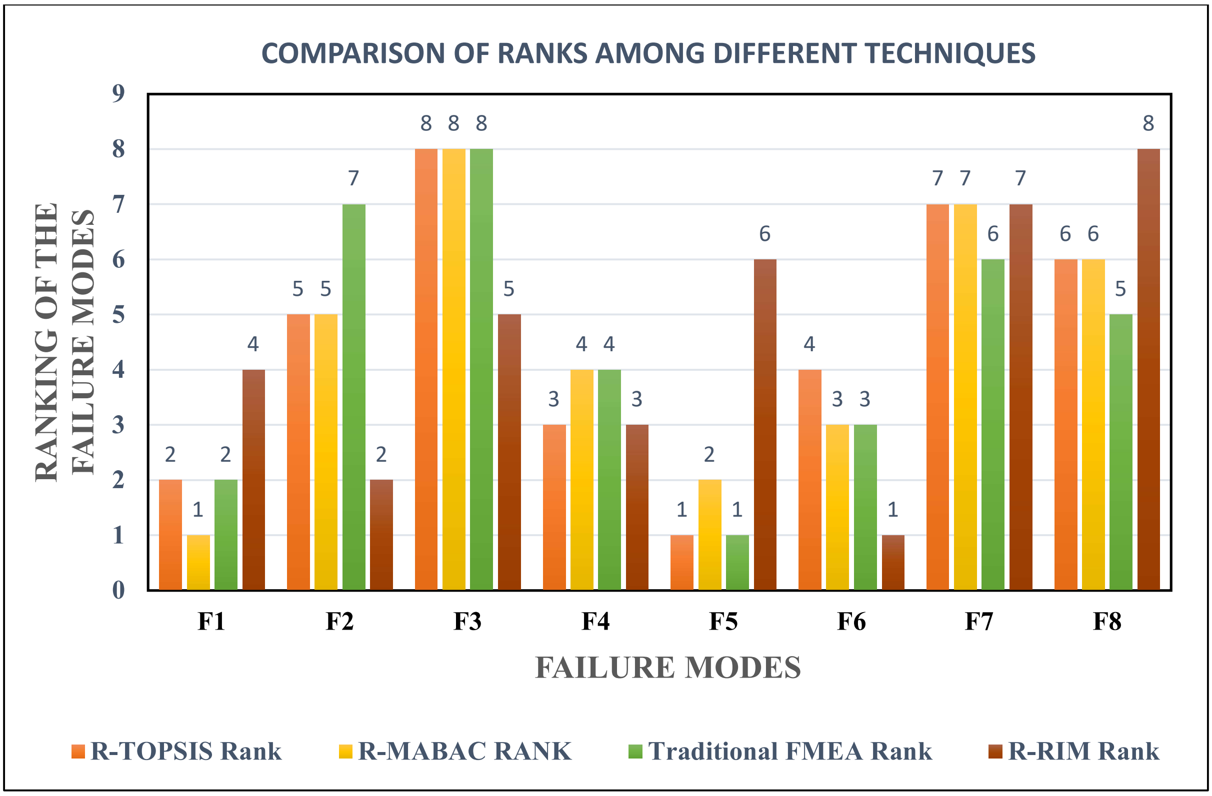

Fig. 6.5 Comparison analysis of the Failure Modes Ranking

Fig. 6.5 shows a notable difference between R-RIM and other methods, especially for Failure modes F 01, F 02, and F 05. Based on the figure above and the functions of all the elements of the Smart AIRP system, it is concluded that, unlike the other methods, the R-RIM method accurately identifies the elements that directly impact consumer health. For example, Failure mode F 06, which is the malfunction of the automatic plunger-type chlorinator, is considered the most significant failure mode. This decision is well justified because improper chlorination in drinking water can cause various health hazards (Gopal et al. 2007) and alter the taste of the water (Sharma et al. 2017). Similarly, Failure mode F 02, the compressor malfunction, could disrupt the oxidation process, hindering the effective removal of arsenic and iron in later stages. Experts strongly support the ranking provided by R-RIM, and others involved with the Smart AIRP system agree with this assessment.

6.4 Sensitivity Analysis

After the completion of the entire mathematical work, the sensitivity analysis was carried out by varying the weightage of the criteria. The idea of the variation has been adopted from Yazdani et al. (2019), and the conditions have been chosen as per the experts' recommendation. The conditions and their respective results have been filled in Table 6.15, and a graphical representation of the same results has been displayed in Fig. 6.6.

Sl. No.	Conditions for Sensitivity of Criteria		Relative Index Values of the respective Failures							
			F1	F2	F3	F4	F5	F6	F7	F8
1	S 10% up	Rest 2.5% Down	0.6366	0.5339	0.7437	0.6329	0.7701	0.4608	0.8608	0.8998
2	D 10% up	Rest 2.5% Down	0.6565	0.5592	0.7085	0.6520	0.7519	0.4979	0.8591	0.8968
3	E 10% up	Rest 2.5% Down	0.6330	0.5485	0.7229	0.6288	0.7619	0.4894	0.8552	0.8913
4	O 10% up	Rest 2.5% Down	0.6438	0.5436	0.7225	0.6391	0.7621	0.4838	0.8524	0.8923
5	C 10% up	Rest 2.5% Down	0.6426	0.5467	0.7247	0.6386	0.7610	0.4821	0.8561	0.8898
6	S 20% up	Rest 5% Down	0.6315	0.5231	0.7610	0.6282	0.7778	0.4416	0.8644	0.9050
7	D 20% up	Rest 5% Down	0.6708	0.5724	0.6924	0.6661	0.7424	0.5136	0.8615	0.8997
8	E 20% up	Rest 5% Down	0.6228	0.5510	0.7208	0.6185	0.7624	0.4972	0.8534	0.8882
9	O 20% up	Rest 5% Down	0.6453	0.5406	0.7200	0.6402	0.7628	0.4855	0.8475	0.8902
10	C 20% up	Rest 5% Down	0.6429	0.5472	0.7246	0.6390	0.7605	0.4818	0.8553	0.8852
11	S 30% up	Rest 7.5% Down	0.6270	0.5136	0.7765	0.6241	0.7848	0.4245	0.8675	0.9097
12	D 30% up	Rest 7.5% Down	0.6852	0.5855	0.6765	0.6803	0.7331	0.5294	0.8639	0.9027
13	E 30% up	Rest 7.5% Down	0.6118	0.5539	0.7185	0.6076	0.7629	0.5057	0.8513	0.8850
14	O 30% up	Rest 7.5% Down	0.6470	0.5372	0.7172	0.6414	0.7637	0.4873	0.8421	0.8878
15	C 30% up	Rest 7.5% Down	0.6432	0.5479	0.7246	0.6395	0.7599	0.4813	0.8543	0.8803
16	S 40% up	Rest 10% Down	0.6232	0.5052	0.7907	0.6206	0.7911	0.4093	0.8702	0.9140
17	D 40% up	Rest 10% Down	0.6996	0.5985	0.6611	0.6946	0.7242	0.5452	0.8664	0.9058
18	E 40% up	Rest 10% Down	0.6002	0.5571	0.7159	0.5960	0.7635	0.5150	0.8491	0.8816
19	O 40% up	Rest 10% Down	0.6490	0.5334	0.7139	0.6428	0.7647	0.4895	0.8362	0.8851
20	C 40% up	Rest 10% Down	0.6435	0.5486	0.7246	0.6401	0.7592	0.4808	0.8532	0.8750

Table 6.15 Parameter-wise Sensitivity Analysis Results

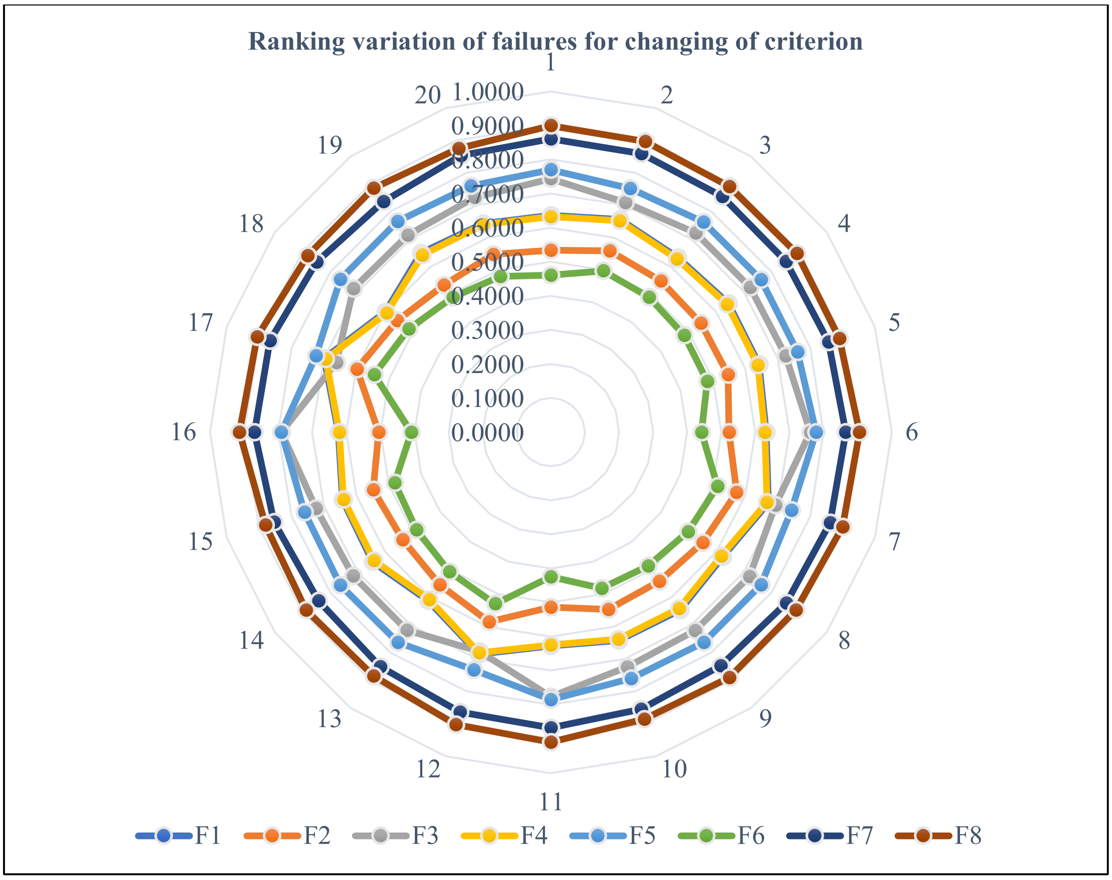

Fig. 6.6 Graphical representation of the Sensitivity analysis

The result of the sensitivity analysis indicates Failure mode F6, i.e. "Malfunction of the Automatic plunger-type chlorinator" as the most severe as well as hazardous failure. It has maintained its top place despite any change in any criterion. Similarly, the F2 has also maintained the second spot throughout the sensitivity study. On the other hand, F8 and F7 have shown their least importance throughout the observation. The discrepancy has been seen in the observation Nos. 12 and 17 among F1, F3 and F4, where criterion "D" has been increased 30% and 40% respectively. It is clear evidence that "D" is a deciding criterion for the said failure mode, where F3 has a negative impact, while F1 and F4 have a positive impact. Overall, the other criteria do not have such significance on the overall result of the analysis.

Chapter 7

Maintenance of an IoT-based WDCS using the FFTA-RCM combined approach

7.1 Introduction

Modern industries are adopting the IoT (Internet of Things) in order to survive in the competitive market under Industry 4.0. IOT is the integration of software, hardware, and network connectivity through which communications are set up between different components in the domain. Some web-enabled devices, i.e. processors, sensors, communication devices, etc., are integrated with a conventional system and its sub-systems from which essential data are collected from a sub-system and sent to other sub-systems in the form of information so that the required action can be taken according to that. The system and the sub-systems can do most of the work without human intervention, though people can interact with the devices, e.g. to set them up, give them instructions or access the data. It provides a real-time look into how the system really works. It is an essential technology nowadays, which continues to advance as more businesses realise the potential of connected devices to keep them competitive. Like all other systems, it also requires maintenance for stability and readiness, for which RCM (Reliability-Centered Maintenance) is a good choice. It is generally a preventive maintenance approach that focuses on optimising the reliability of a system or process. It is technically an authentic process which focuses on the root cause of the failure of the system and maintenance operation conducted by focusing on these failures along with Mode of failures, criticality of the system and potential consequences. The fundamental of RCM can be sub-divided into three phases namely **i) Decision**, where the factors which influence a system has been identified, **ii) Analysis**, where the root cause of the factors influence the systems are identified and appropriate maintenance are adopted accordingly and lastly **iii) Outcomes and feedback**, where the result obtained from maintenance program are analyzed and based on analysis proper task are carried out for further improvement of the system. From the basics of RCM, it may conclude that sufficient failure data are required in order to adopt RCM strategy. However, due to the unavailability of sufficient failure data, RCM adaptation becomes unrealizable. FFTA (Fuzzy Fault Tree Analysis) Plays a revival role under these circumstances. Its emphasis on qualitative failure data from experts in the respective fields and converted them to numerical values for further evaluation. A detail discussion on FFTA and RCM along with detail literature reviews has discussed on the later part. But the basic question may arise that what is the significance of this study? At a glance, the prime moto of the FFTA is to identify and recognize the most vulnerable component of a system using FTA and convert the expert’s elicitation regarding failure of the components and system into a suitable numeric value using the fuzzy logic. On the basis of the failure data, the reliability of the system has been calculated and said values are the prime sources of RCM technique for setting up a suitable maintenance strategy. The framework of the research can be understand using a Venn diagram as shown in fig. 7.1. Several literature surveys have been conducted on both RCM and FFTA which has been discussed in the theory part. Through the literature survey, it has been observed as a noble and holistic approach which combine the both RCM and FFTA in a single framework and on the other hand it has also found that no such approach has been initiated on the IoT system in order to adopt the proper maintenance strategy under uncertain and unstructured environment. The practical implication of the study is to augment the system availability into a large extent in order to improve the growth and development of the respective organization as a whole. The basic idea of the system considered as the case study, has been delved.

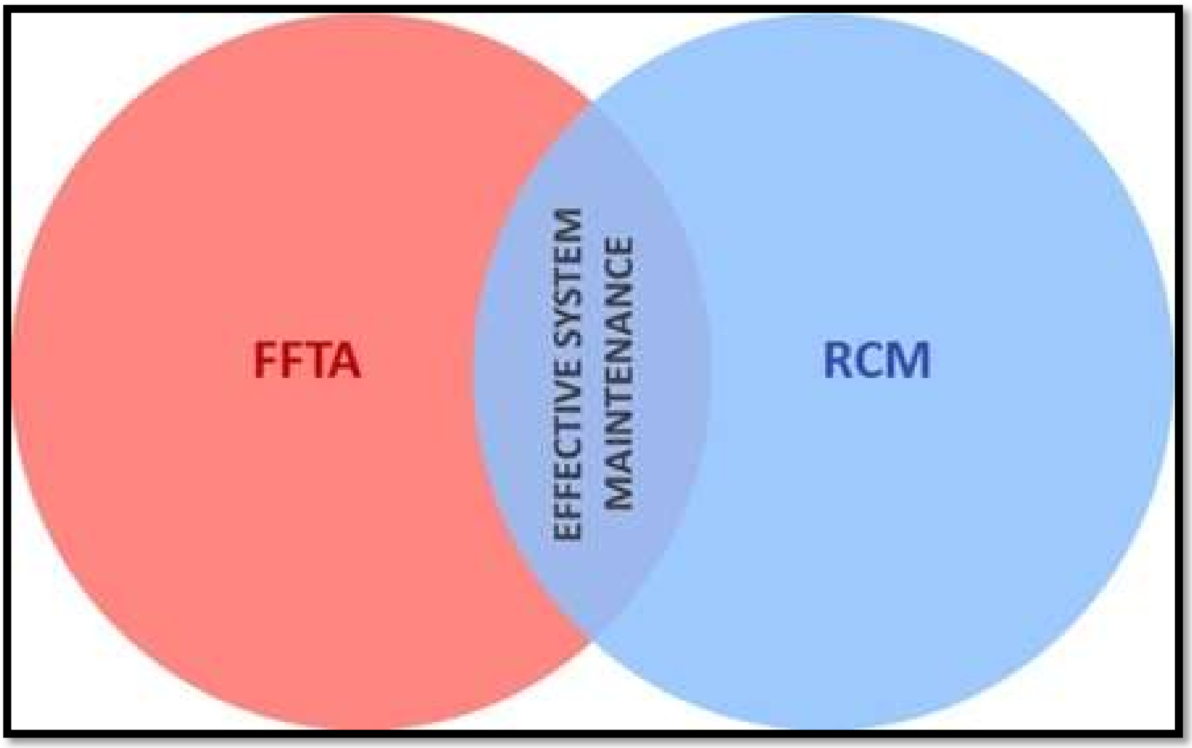

Fig. 7.1 Venn Diagram of the Proposed Research work

7.1.1 System Overview

During data collection for research work, the concept of the said system has been adopted from a leading Indian manufacturing company of aluminium and its associated product. The data regarding weights carried by an ECL (Electrification Charpente Levage) crane, which is basically an overhead crane used in the aluminium smelting plant, is available at a printer set up inside the crane. There is no provision for digital data backup for future reference. Thus, obtaining weight data for the requisite period is a difficult and laborious task, which hampers the production system. Due to the massive height of the crane, the regular inspection as well as the collection of data is a matter of safety concern. Considering the said factors, an IoT-based weight data communication system has been adopted. This system systematically stores the data in the database system for any future reference and reflects the exact weight data information at the ground station. A typical block diagram of the system is pictured in Fig. 7.2. The weight information handled by the ECL crane is measured by the weight sensor and transmitted to the weight processor. This information is converted to a current signal having a range from 0 to 20mA and received by a current loop converter. This device is attached either to a printer through a 25-pin serial connector for printing the weight value or to a display board for showing the weight. However, due to the availability of the weight data at the ground station as well as to store the digital data in the organizational database, the IOT system has been adopted. As Fig. 7.2 shows, another current loop converter is connected in series with a weight processor. Likewise, the first one also received the current signal and transferred it into a pocket-sized computer, which is the prime communication device of the system. The transmission of the signal is processed through a 25-pin serial to a 9-pin serial and then through a USB converter, which is powered up by a 12-volt external DC source. The data is transferred from the communication device to the ground station through Wi-Fi. A combination of programs written in Python script along with MySQL (My Structured Query Language), a database management system, set up the communication between both cranes and the ground station. Both cranes are configured as Master-Master replication in the MySQL database system. On the other side, the ground station is configured as Master-slave replication with either of the cranes in MySQL. In case of any failure in the wireless communication system, the ground station will get synchronized as the connection is ready. This leads to the elimination of data loss due to network failure. The ground station has an open-source PHP (Personal Home page, currently known as Hypertext Pre-Processor) server, which is programmed to fetch weight data from a MySQL database. This system provides basic knowledge of an IOT system along with its predominance over conventional systems. But one thing has to be understood: this is also an engineering system that comprises various types and modes of failures. While reviewing the system, the possible grounds of failure have been identified & discussed in the next section.

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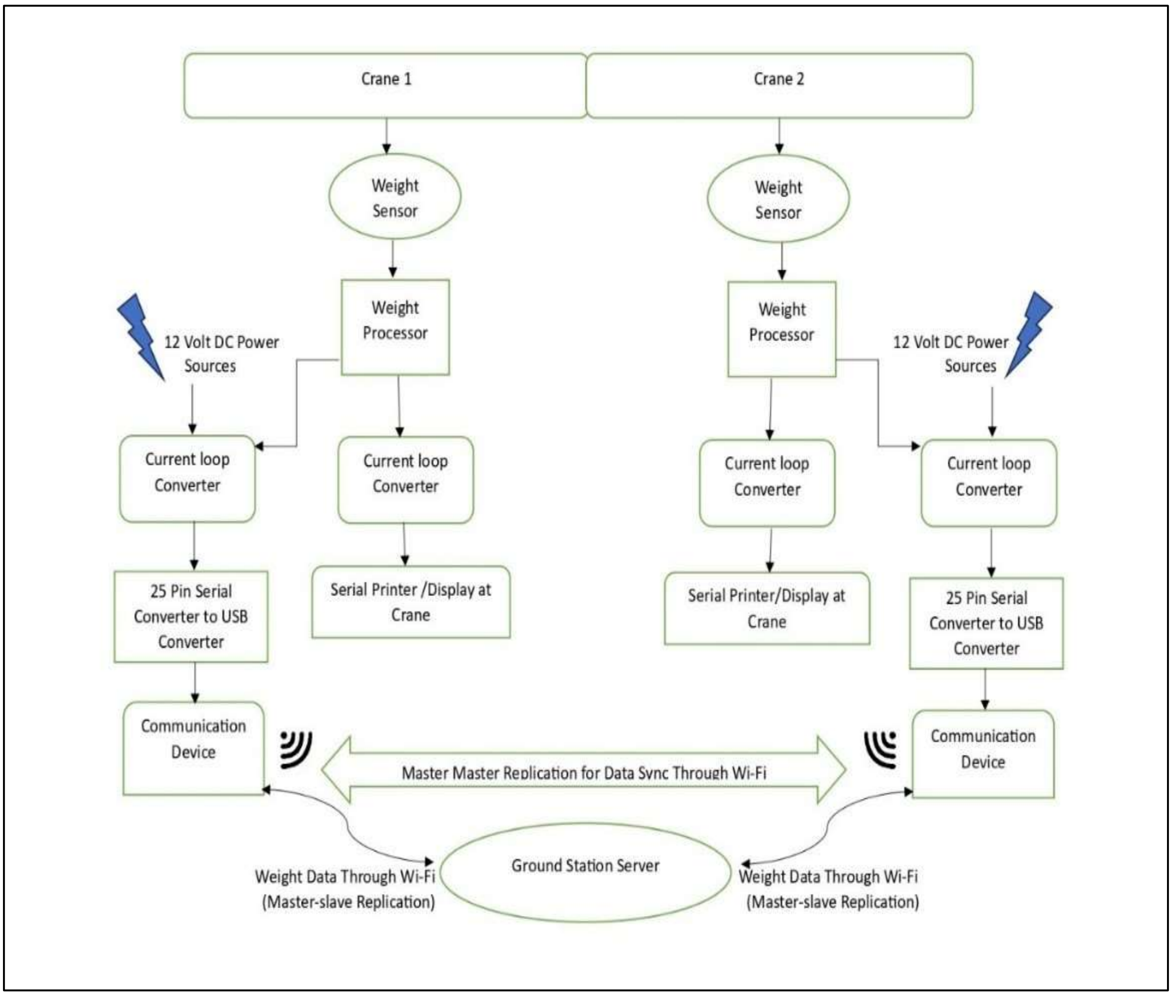

Fig. 7.2 Schematic Diagram of IoT-based weight data communication system

7.1.2 Fuzzy fault tree analysis (FFTA)

The concept of FFTA is based on two different topics. First weightage has been given to FTA, which is a powerful tool to identify how the system may fail to function. It is a deductive or backwards analysis, as stated by Kabir (2017). The term "tree" implies the shape of the logic diagram, which consists of nodes and branches (Srinath, 1991). This tool has extensive use in computing system reliability. It uses both qualitative and quantitative assessments to trace system failure. The causes of system failure are analyzed and gradually split into hierarchical levels until the effect of component failure can be identified (Billinton, 1992). But in real-life situations, due to a shortage of useful failure data, the analysis of the effective life of a system becomes very difficult. Under this uncertain environment, fuzzy set theory performs a key role by extracting calculable essence from qualitative data based on this idea. The idea of this theory was proposed by Prof. L. A. Zadeh (1965). This theory is extensively used in two situations, either for the analysis of a complex system with an uncertain behaviour or for a case where an inferential but rapid solution is required (Ross, 2009). A fuzzy number or fuzzy probability is an imprecise form of a real number. The weight of imprecision varies from 0 to 1, which is known as the membership function. A fuzzy number represents itself in the probability space under a fuzzy set with a value ranging from 0 to 1. A triangular fuzzy number (TFN) and its membership function are illustrated in Fig. 7.3 along with its membership function (Dey et al. 2016). f(x) is the membership function of the triangular fuzzy no as drawn above and expressed as:

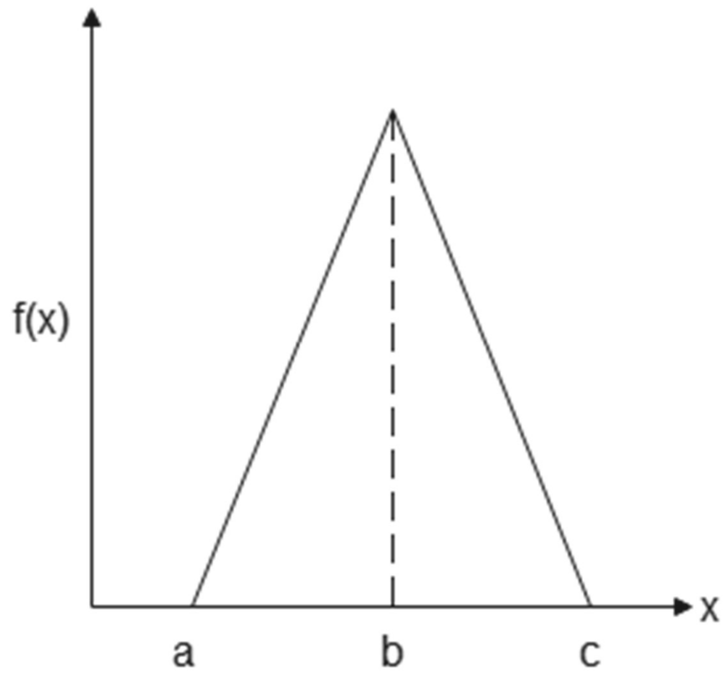

Fig. 7.3 TFN and its membership function

$$f(x) = \begin{cases} \frac{x-a}{b-a}, a \le x \le b \\ \frac{c-x}{c-b}, \ b \le x \le c \\ 0, \ otherwise \end{cases} \tag{7.1}$$

The extraction of crisp values from qualitative parameters in the field of reliability analysis using fuzzy theory has been adopted by various researchers, which are explicitly mentioned in the respective literature review. Based on those literature reviews, it is found that FFTA comes out as an effective tool for FP calculation under uncertain environments. Based on the assumption, FFTA has been incorporated in this study for the calculation of the FP of BEs of the said IOT system. A Fault tree (FT) diagram of the IOT system has been illustrated in Fig. 7.4 to identify the elemental failure of the system. Table 7.1 discusses particulars of different failures as drawn in FT.

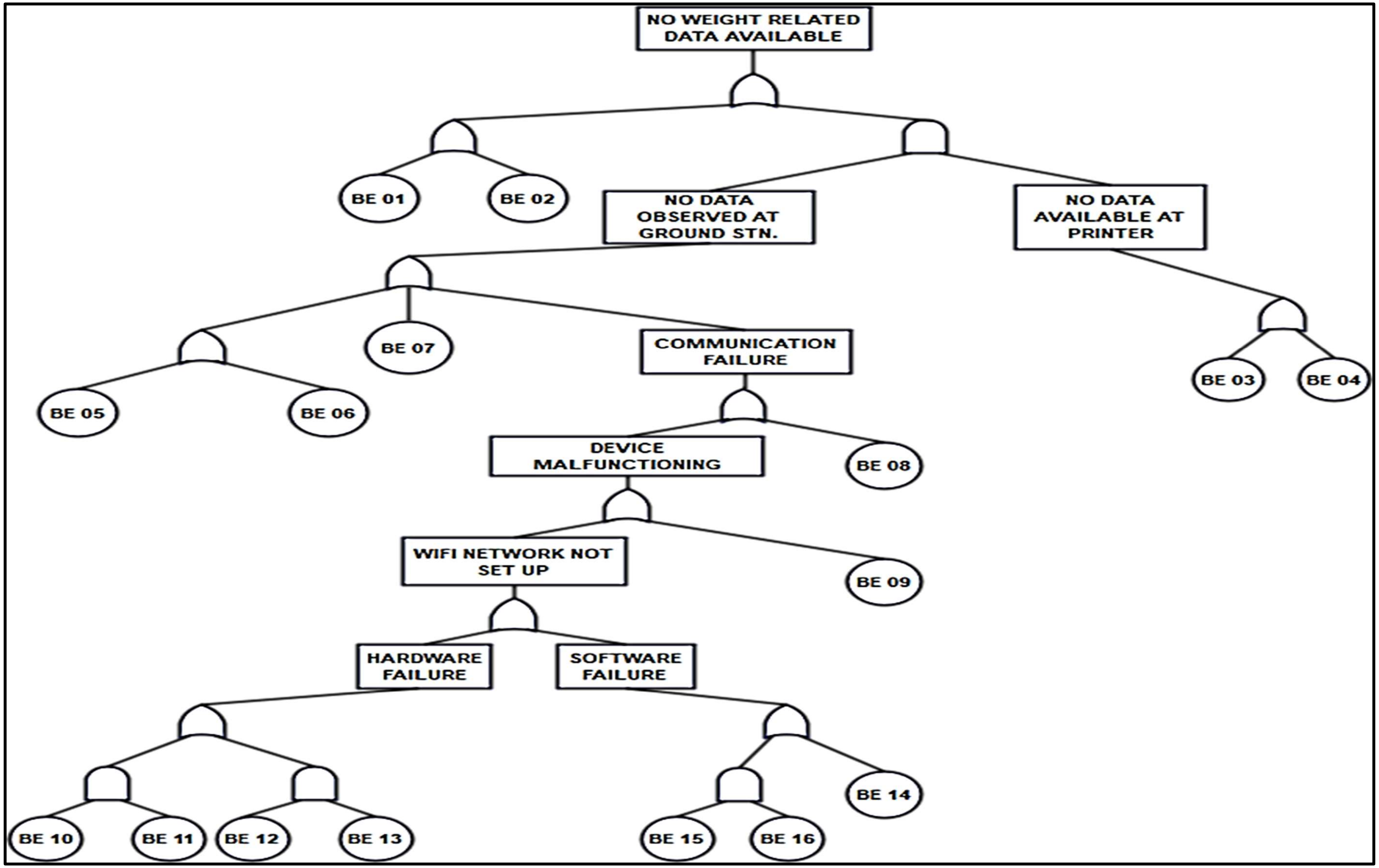

Fig. 7.4 Fault tree diagram of IoT-based weight data communication system [72]

BEs	PARTICULARS
F1	WT SENSORS FAILURE
F2	WT PROCESSOR FAILURE
F3	CURRENT LOOP CONVERTER FAILURE
F4	PRINTER FAILURE
F5	CURRENT LOOP CONVERTER NO. 2 FAILURE
F6	12 VOLT DC POWER SOURCE FAILURE
F7	25 PIN SERIAL to USB CONVERTER FAILURE
F8	POWER FAILURE OF COMMUNICATION DEVICE
F9	WIFI CHIP FAILURE OF COMMUNICATION DEVICE
F10	GROUND STATION POWER FAILURE
F11	BACKUP CRANE FAILURE
F12	GROUND STATION WIFI RECEIVER FAILURE
F13	BACKUP CRANE WIFI RECEIVER FAILURE
F14	SOFTWARE FAILURE DUE TO MALWARE ATTACK
F15	SOFTWARE FAILURE: M-TO-M SYNCHRONIZATION
F16	SOFTWARE FAILURE: M-TO-S SYNCHRONIZATION

Table 7.1 Particulars of different failures in the FT

7.1.3 Reliability-Centered Maintenance (RCM)

RCM is a mode of optimal maintenance through which a system can carry out its designed function under a normal operating environment. Safety is the primary aim of RCM, followed by reliability, availability, and cost-effectiveness of the system (Okwuobi, 2018). Henceforth, this ensures the stabilization of the inherent reliability of the system. The selection of preventive maintenance strategies is based on the probability of failure modes and their consequences (Samanta, 2001). Preventive maintenance aims to secure the system before it fails (Werbińska-Wojciechowska, 2019). It either follows a schedule or is determined by the condition of the system (Jimenez, 2020). RCM methodology puts in the preventive maintenance action in a structured manner to extend the service life of the system. This method found a unique paradigm over other maintenance strategies and was adopted in different engineering fields, as discussed in the systematic literature review section. RCM implies the reduction of maintenance costs by improving the Availability of the system. The above literature reviews signify the effectiveness of RCM in finding effective maintenance strategies based on the failure probability of the system, as well as in minimizing downtime, which signifies the improvement of system availability.

Both FFTA and RCM have been found useful in their respective domain, and considering their merits and demerits, a collaborative approach has been set up between them to select the correct maintenance strategy for the IoT-based data communication system during its operation.

7.2 Methodology

The basic methodology of this research work consists of two parts, as stated before. A flowchart of the work has been constructed and portrayed in Fig. 7.5. First, three steps of the block diagram were already covered by the introductory part. After constructing the FT diagram, the basic failure events have been identified. The FFTA has been conducted through the following stages, as discussed.

7.2.1 Rating and weightage stage

A group of four experts from the relevant field, having sound knowledge of the system, was invited for their valuable opinions regarding the failure of respective IOT systems. The score rating criteria of the experts are represented in Table 7.2. Based on the assigned score expressed in Table 7.2, the assigned score (x_i) of each expert has been computed and tabulated in Table 7.3. The Sum of the assigned score $(\sum x_i)$has also been evaluated to find the weightage associated with each expert. Henceforth, the weightage, $W(E_u)$, of each expert has been presented in Table 7.4. The linguistic rating of FP based on the expert's judgment has been collected at different periods for all BEs. In this study, the periods are considered as 2500 Hours, 5000 Hours, 7500 Hours, and 10000 Hours, respectively. Experts' decisions corresponding to each period are reflected in Table 7.5.

P.T.O

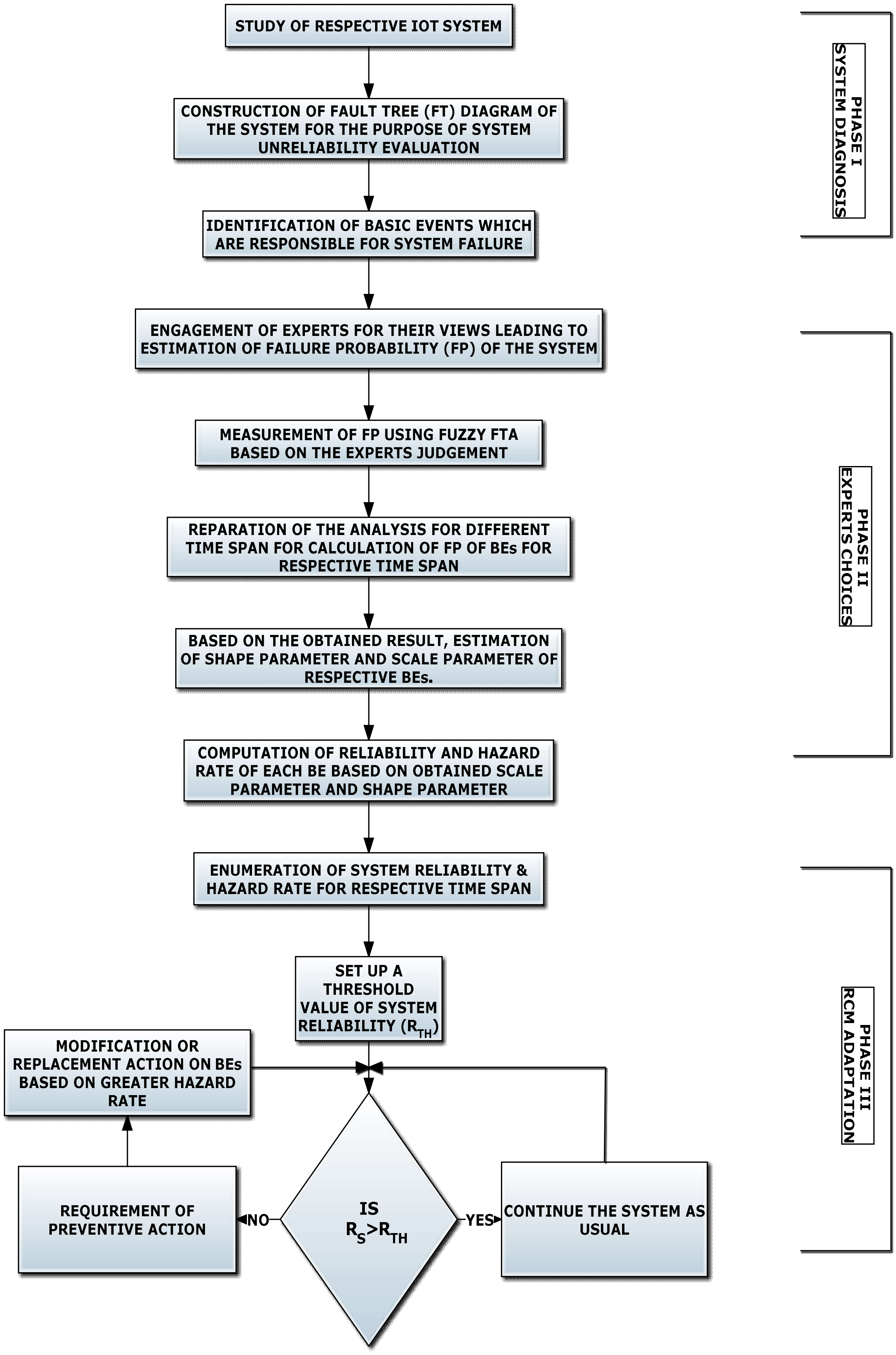

Fig. 7.5 Flow chart of the research work

Sl. No.	Criterion	Category	Score
1.	Designation	General Manager (GM)/Dy. GM/Professor	5
		AGM/Associate Professor	4
		Sr. Manager/Senior Researcher/Assistant Professor	3
		Assistant Manager/Foreman/Lecturer	2
		Junior Researcher/Supervisor	1
2.	Job/Research Experience	Over 30 Years	4
		21-30 Years	3
		11-20 Years	2
		10 and below 10 years	1
3.	Qualification	PhD and Above	4
		M.E/M. Tech/M.B.A	3
		B.E/B. Tech	2
		Diploma Engineering	1
4.	Time of involvement with the Job-shop activity	More than 50 Hours/Week	4
		30 to 50 Hours/Week	3
		15 to 29 Hours/Week	2
		Less than 15 Hours/Week	1

Table 7.2 The rating of experts based on criteria

Expert (E)	Designation	Job/Research Experience	Qualification	Time of involvement with the Job-shop activity	Assign Score (x_i)
1	Dy. GM (R&D) (Score: 5)	25 Years (Score: 3)	M.E (Score: 3)	18 Hours/ Week (Score: 2)	13
2	Professor (Industrial Engineering) (Score: 5)	32 Years (Score: 4)	PhD (Score: 4)	6 Hours/Week (Score: 1)	14
3	Senior Researcher (Score: 3)	5 Years (Score: 1)	M. Tech (Score: 3)	36 Hours/ Week (Score: 3)	10
4	Sr. Manager (Score: 3)	16 Years (Score: 2)	M. Tech (Score: 3)	55 Hours/Week (Score: 4)	12
The sum of Assign Score $(\sum x_i)$					**49**

Table 7.3 Assigned score of the Experts

Expert (E_u)	1	2	3	4
Weightage $(\frac{x_i}{\sum x_i})$	0.265	0.286	0.204	0.245

Table 7.4 Weightage of each expert

BEs	2500 Hours				5000 Hours				7500 Hours				10000 Hours			
	E1	**E2**	**E3**	**E4**	**E1**	**E2**	**E3**	**E4**	**E1**	**E2**	**E3**	**E4**	**E1**	**E2**	**E3**	**E4**
F1	M	M	H	M	M	H	VH	H	H	VH	VH	VH	VH	EH	EH	VH
F2	M	M	M	H	H	VH	H	H	H	VH	VH	VH	VH	EH	VH	EH
F3	M	L	M	M	H	M	M	H	VH	H	H	H	VH	VH	VH	VH
F4	VL	L	L	VL	L	L	M	L	M	M	M	M	H	H	M	M
F5	M	L	M	M	H	M	M	H	VH	H	H	H	VH	VH	VH	VH
F6	M	M	M	M	H	H	H	M	VH	VH	VH	VH	EH	VH	EH	EH
F7	M	L	L	M	H	M	M	M	H	H	H	H	VH	H	VH	H
F8	VL	EL	EL	VL	VL	VL	VL	VL	L	L	VL	L	L	M	L	L
F9	VL	EL	L	VL	VL	VL	L	L	L	L	M	L	M	M	M	M
F10	VL	VL	VL	VL	L	VL	VL	L	M	L	L	L	M	L	M	M
F11	L	L	VL	VL	M	L	VL	L	M	L	L	M	M	M	L	H
F12	VL	VL	L	VL	VL	L	L	VL	L	M	M	L	M	M	H	L
F13	L	VL	L	VL	L	L	L	L	M	L	L	M	H	M	M	M
F14	L	M	L	VL	L	M	M	L	M	M	M	L	M	M	M	M
F15	EL	EL	EL	EL	EL	EL	EL	VL	VL	EL	EL	VL	VL	VL	VL	VL
F16	EL	EL	EL	EL	EL	EL	EL	VL	VL	EL	EL	VL	VL	VL	VL	VL

Table 7.5 Decision provided by the experts for different periods in linguistic terms
[78]

7.2.2 Selection of fuzzy Numbers and membership function

Numerous fuzzy numbers are used by different researchers working in different fields. But Triangular fuzzy Number (TFN) and Trapezoidal fuzzy Number (TZFN) are best suited for reliability analysis (Mahmood, 2013). After studying different literature reviews, TFN finds a suitable choice for its simplicity as well as effectiveness (Herrera, 2005). A fuzzy set with seven linguistic representations has been considered in this study for precise calculation (Chen, 2008). The TFN of each linguistic expression is tabulated in Table 7.6.

Sl. No.	Linguistic representation	TFN
1	Extremely Low (EL)	(0,0,0.17)
2	Very Low (VL)	(0,0.17,0.33)
3	Low (L)	(0.17,0.33,0.5)
4	Medium (M)	(0.33,0.5,0.67)
5	High (H)	(0.5,0.67,0.83)
6	Very High (VH)	(0.67,0.83,1)
7	Extremely High (EH)	(0.83,1,1)

Table 7.6 Linguistic expression of TFN

The linguistic representations of fuzzy numbers have been reflected in Fig. 7.6. Based on the linguistic response proposed by the experts, aggregation of linguistic expressions has been conducted.

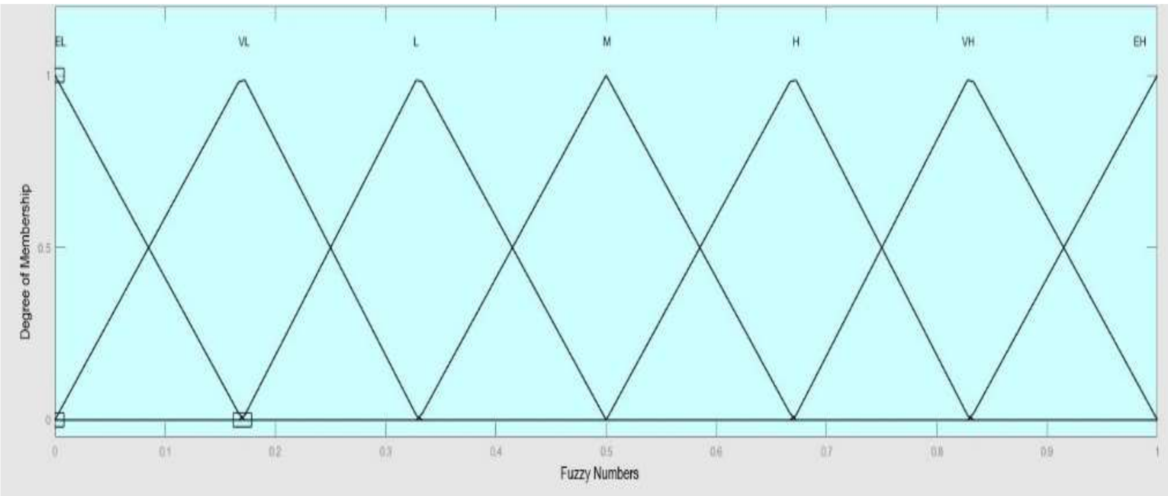

Fig 7.6 Linguistic representation of failure probability

7.2.3 Aggregation of basic events

The steps associated with fuzzification and aggregation of linguistic expressions in FFTA are discussed below:

Step 1: Enumerating the degree of similarity between a pair of experts

It is defined as the closeness of judgment between a pair of experts out of j number of experts on the same event. Suppose an expert E_1 proposed a judgment $J_1 = (a_1, a_2, a_3)$ for an event and expert E_2 proposed a judgment $J_2 = (b_1, b_2, b_3)$ for the same event. The degree of similarity between the pair of experts, S (J_1, J_2), is defined as:

$S\,(J_1, J_2) = 1 - \frac{1}{J}\sum_{i=1}^{J}|a_i - b_i|$, Where, i = 1,2,3 (7.2)

Step 2: Calculating the Average Agreement (AA) degree of an expert

This step computes the average value of the degree of similarity of an expert concerning the rest of the experts for the same event. Suppose there are four experts, namely E_1, E_2, E_3, and E_4, and their judgments on the same event are J_1, J_2, J_3, and J_4, respectively. The average agreement (AA) degree of E_1 can be written as:

$AA(E_1) = \frac{1}{j-1}\,[S\,(J_1, J_2) + S\,(J_1, J_3) + S\,(J_1, J_4)]$, where j = No. of Experts

The general expression of the Average of Agreement (AA) degree can be written as:

$$AA(E_u) = \frac{1}{j-1}\sum_{\substack{u \neq v \\ v=1}}^{j} S(J_u, J_v) \tag{7.3}$$

Step 3: Computing the Relative Agreement (RA) degree of all experts

The general expression of the Relative Agreement (RA) degree can be manifested as:

$$RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{j} AA(E_u)} \tag{7.4}$$

Step 4: Calculating the Consensus coefficient (CC) of an expert

While calculating the Consensus coefficient (CC), a term called relaxation factor (γ) has to be considered. The range of (γ) varies from 0 to 1 i.e. $[0 \leq \gamma \leq 1]$. The consensus coefficient (CC) of an expert can be estimated as:

$$CC(E_u) = \gamma . W(E_u) + (1 - \gamma) . RA(E_u) \tag{7.5}$$

It maintains a balance between weightage, $W(E_u)$, and relative agreement, $RA(E_u)$ during the calculation of (CC). So, the precise value of γ should be considered during calculation. In the case of equal weightage, the value of γ has been considered as 0.5, and this consideration has also been adopted in this work.

Step 5: Computing the aggregated result of the expert's judgment, R_{AG}

The value of R_{AG} for each event can be computed as:

$$R_{AG} = \sum_{u=1}^{j} CC(E_u).J_u \quad (7.6)$$

The de-fuzzification of each BE would start after enumerating the R_{AG} of each event.

7.2.4 Defuzzification and Computation of FP

Defuzzification implies the conversion of fuzzy numbers into crisp numbers. Several methods are available for the calculation of crisp value. In this work, the conversion of TFN to the corresponding crisp value is inspired by BAN et al. (2020), as it was found to be more precise compared to others. Suppose the R_{AG} of an event is represented by (x, y, z) Then the Corresponding crisp value X' will be:

$$X' = \frac{(x+2y+z)}{4} \quad (7.7)$$

The crisp value is vital for the computation of FP based on the following formulae used by Badida et al. (2019).

$$k = [(\frac{1}{X'} - 1)^{\frac{1}{3}}] \times 2.301 \quad (7.8)$$

$$FP = \frac{1}{10^k} \quad (7.9)$$

Weibull distribution has been considered as a probability distribution function for all BEs, to compute reliability as well as the Hazard rate. Weibull distribution, due to its indistinct characteristic shape as well as to fit experimental data that are not characterized by any distributions, has a sound abidance (Billinton, 1992). FP of the two-parameter Weibull distribution written as:

$$FP = 1 - exp^{[-\left(\frac{t}{\alpha}\right)^{\beta}]} \quad (7.10)$$

Where β, α are the shape parameter and scale parameters, respectively & t represents the time corresponding to FP

To compute the values of the shape parameter and scale parameter, both FP and corresponding time are plotted in a Weibull probability graph paper as suggested by Kumar et al. (2017). The axis of the graph is:

$$x\ axis = \ln(t) \tag{7.11}$$

$$y\ axis = \ln\left[\ln\left(\frac{1}{1-FP}\right)\right] \tag{7.12}$$

The values are put into an Excel sheet, which constructs a best-fitted straight line as well as provides its equation through which both parameters have been calculated.

6.4.5 Reliability (R) and Hazard Rate (λ) Calculation

Reliability (R) implies the probability of successful operation of a system for a specific period under a given operating condition. This indicates, $R(t) = (1 - FP)$. Therefore, reliability in terms of the formula can be written as:

$$R(t) = exp^{\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right]} \tag{7.13}$$

Hazard Rate (λ) is defined as the instantaneous failure rate of the system per unit time. It can be written as:

$$\lambda = \frac{\beta t^{\beta-1}}{\alpha^{\beta}} \tag{7.14}$$

7.2.5 Adaptation of RCM strategy

After enumerating the values of R and λ for all BEs for different periods, the system reliability (R_s) and system hazard rate (λ_s) have been computed and plotted against the said periods to observe the nature of the plotting and also to calculate intermediate values. The concept of Boolean algebra in terms of logic gates, namely the OR gate and AND gate, is considered for the construction of FT. The equation of reliability and hazard rate for the OR gate is given by equations 7.15 and 7.16, respectively. Similarly, the Equation of reliability and hazard rate for the AND gate is presented in equations 7.17 and 7.18, respectively (Boland, 1997).

$$R(t) = \prod_{i=1}^{m} R_i(t) \tag{7.15}$$

$$\lambda(t) = \sum_{i=1}^{m} \lambda_i(t) \tag{7.16}$$

$$R(t) = 1 - \prod_{i=1}^{m}[1 - R_i(t)] \tag{7.17}$$

$$\lambda(t) = \sum_{i=1}^{m} \lambda_i(t) \frac{R_i(t)}{1-R_i(t)} \left(\frac{\prod_{j=1}^{m}(1-R_j(t))}{1-\prod_{j=1}^{m}(1-R_j(t))} \right) \quad (7.18)$$

A threshold value R_{TH} of system reliability has been established by industrial experts, design engineers, maintenance engineers, and manufacturers' viewpoints. Preventive maintenance action would be immediately initiated once the threshold value found is greater than the system reliability (R_S). The element responsible for BEs having the highest hazard rate value will be replaced with a new one for system sustainability.

7.3 Findings and Contributions

7.3.1 Result of FP using FFTA

The result of FP has been obtained after numerous calculations based on the equations stated above. The results against 2500 Hours of operation have been discussed herewith. The degree of similarity among the experts has been furnished in Table 7.7. The average of the Agreement (AA) degree of each expert furnished in Table 7.8 has been computed vide equation 7.3.

BEs	S(E1 ,E2)	S(E1, E3)	S(E1, E4)	S(E2, E3)	S(E2, E4)	S(E3, E4)
F1	1	0.833333	1	0.833333	1	0.833333
F2	1	1	0.833333	1	0.833333	0.833333
F3	0.833333	1	1	0.833333	0.833333	1
F4	0.833333	0.833333	1	1	0.833333	0.833333
F5	0.833333	1	1	0.833333	0.833333	1
F6	1	1	1	1	1	1
F7	0.833333	0.833333	1	1	0.833333	0.833333
F8	0.89	0.89	1	1	0.89	0.89
F9	0.89	0.833333	1	0.723333	0.89	0.833333
F10	1	1	1	1	1	1
F11	1	0.833333	0.833333	0.833333	0.833333	1
F12	1	0.833333	1	0.833333	1	0.833333

BEs	S(E1 ,E2)	S(E1, E3)	S(E1, E4)	S(E2, E3)	S(E2, E4)	S(E3, E4)
F13	0.833333	1	0.833333	0.833333	1	0.833333
F14	0.833333	1	0.833333	0.833333	0.666667	0.833333
F15	1	1	1	1	1	1
F16	1	1	1	1	1	1

Table 7.7 Degree of similarity between pairs of experts

BEs	AA(E1)	AA(E2)	AA(E3)	AA(E4)
F1	0.944444	0.944444	0.833333	0.944444
F2	0.944444	0.944444	0.944444	0.833333
F3	0.944444	0.833333	0.944444	0.944444
F4	0.888889	0.888889	0.888889	0.888889
F5	0.944444	0.833333	0.944444	0.944444
F6	1	1	1	1
F7	0.888889	0.888889	0.888889	0.888889
F8	0.926667	0.926667	0.926667	0.926667
F9	0.907778	0.834444	0.796667	0.907778
F10	1	1	1	1
F11	0.888889	0.888889	0.888889	0.888889
F12	0.944444	0.944444	0.833333	0.944444
F13	0.888889	0.888889	0.888889	0.888889
F14	0.888889	0.777778	0.888889	0.777778
F15	1	1	1	1
F16	1	1	1	1

Table 7.8 Average of Agreement (AA) degree of each expert

After obtaining the AA of experts, the Relative Agreement (RA) degree of every expert is evaluated based on equation 7.4 and put into Table 7.9.

BEs	RA(E1)	RA(E2)	RA(E3)	RA(E4)
F1	0.257576	0.257576	0.227273	0.257576
F2	0.257576	0.257576	0.257576	0.227273
F3	0.257576	0.227273	0.257576	0.257576
F4	0.25	0.25	0.25	0.25
F5	0.257576	0.227273	0.257576	0.257576
F6	0.25	0.25	0.25	0.25
F7	0.25	0.25	0.25	0.25
F8	0.25	0.25	0.25	0.25
F9	0.263378	0.242102	0.231141	0.263378
F10	0.25	0.25	0.25	0.25
F11	0.25	0.25	0.25	0.25
F12	0.257576	0.257576	0.227273	0.257576
F13	0.25	0.25	0.25	0.25
F14	0.266667	0.233333	0.266667	0.233333
F15	0.25	0.25	0.25	0.25
F16	0.25	0.25	0.25	0.25

Table 7.9 Relative Agreement (RA) degree of each expert

Based on the calculated value of RA from Table 7.9 and the weightage of the experts in Table 7.4, Consensus coefficient (CC) values are evaluated by considering equation 7.5. The CC values of the experts are furnished in Table 7.10.

BEs	CC (E1)	CC (E2)	CC (E3)	CC(E4)
F1	0.2613	0.2718	0.2156	0.2513
F2	0.2613	0.2718	0.2308	0.2361
F3	0.2613	0.2566	0.2308	0.2513
F4	0.2575	0.2680	0.2270	0.2475
F5	0.2613	0.2566	0.2308	0.2513
F6	0.2575	0.2680	0.2270	0.2475
F7	0.2575	0.2680	0.2270	0.2475
F8	0.2575	0.2680	0.2270	0.2475
F9	0.2642	0.2641	0.2176	0.2542
F10	0.2575	0.2680	0.2270	0.2475
F11	0.2575	0.2680	0.2270	0.2475
F12	0.2613	0.2718	0.2156	0.2513
F13	0.2575	0.2680	0.2270	0.2475
F14	0.2658	0.2597	0.2353	0.2392
F15	0.2575	0.2680	0.2270	0.2475
F16	0.2575	0.2680	0.2270	0.2475

Table 7.10 CC values of Experts

The aggregated result of the expert's judgment (R_{AG}) is the value that is useful for the calculation of a crisp value for all the BEs. The value of R_{AG} is obtained by following equation 7.6. From Table 7.5, it can be seen that E1, E2, E3, and E4 have opted for F1 as Medium, Medium, High, and Medium, respectively, for 2500 Hours. Based on the respective TFN as shown in Table 7.6, the values are tabulated in Table 7.11.

BEs	Aggregation of Triangular fuzzy number		
F1	0.3667	0.5367	0.7045
F2	0.3701	0.5401	0.7078
F3	0.2889	0.4564	0.6264
F4	0.0842	0.2492	0.4142
F5	0.2889	0.4564	0.6264
F6	0.3300	0.5000	0.6700
F7	0.2508	0.4159	0.5859
F8	0.0000	0.0859	0.2508
F9	0.0370	0.1599	0.3247
F10	0.0000	0.1700	0.3300
F11	0.0893	0.2541	0.4193
F12	0.0367	0.2045	0.3667
F13	0.0824	0.2475	0.4124
F14	0.1709	0.3359	0.5035
F15	0.0000	0.0000	0.1700
F16	0.0000	0.0000	0.1700

Table 7.11 Aggregated result of the expert's judgment (R_{AG})

Finally, the FP values of BEs are derived considering equations 7.7 to 7.9 and furnished in Table 7.12. The numerical framework of F1 has been given below.

$$X' = \left\{\frac{0.3667 + 2 * 0.5367 + 0.7045}{4}\right\} = 0.53612$$

$$k = [(\frac{1}{0.53612} - 1)^{\frac{1}{3}}] \times 2.301 = 2.19263$$

$$FP = \frac{1}{10^{2.19263}} = 0.006417585$$

BEs	X’	K	FP
F1	0.53612	2.19263	0.006417585
F2	0.53955	2.18256	0.006568177
F3	0.45701	2.43708	0.003655264
F4	0.24918	3.32349	0.000474796
F5	0.45701	2.43708	0.003655264
F6	0.50000	2.30100	0.005000345
F7	0.41709	2.57262	0.002675357
F8	0.10563	4.68994	2.042E-05
F9	0.17039	3.89993	0.000125912
F10	0.16750	3.92681	0.000118356
F11	0.25421	3.29402	0.000508134
F12	0.20308	3.62938	0.000234758
F13	0.24744	3.33379	0.00046367
F14	0.33653	2.88524	0.001302458
F15	0.04250	6.49880	3.17102E-07
F16	0.04250	6.49880	3.17102E-07

Table 7.12 FP values of BEs

7.3.2 Estimation of Reliability (R) and Hazard Rate (λ)

The values of R and λ are obtained from equations 7.13 and 7.14, respectively, which are insoluble due to obscure values of β and α. Under these circumstances, those values are tracked from the Weibull probability graph paper. Equations 7.11 and 7.12 indicate the x-axis and y-axis of the graph, respectively. To solve those equations, Period, and adjacent FP of all BEs are required. Likewise, previous method, the FP of all BEs has been evaluated for 5000, 7500, and 10000 Hours, respectively. For example, the FP of F1 for 5000 Hours has been evaluated as 0.014470, and similarly, for 7500 Hours and 10000 Hours, the FP values have appeared as

0.0335832 and 0.0743145, respectively. An Excel sheet has been utilized to calculate and plot the graph, and it also indicates the equation of the trend line. and the details calculation for F1 has been provided below.

$$x\ axis = \ln(2500) = 7.824046$$

$$y\ axis = \ln\left[\ln\left(\frac{1}{1 - 0.006417585}\right)\right] = -5.04549598$$

Continuing the same process for 5000,7500, and 10000 Hours as stated before, the Weibull distribution graph has been constructed by plotting the points. Considering the trend line, the equation has been generated from Microsoft Excel Software as stated above. Using the equation of the straight line, the values of β and α have been computed. Weibull distribution plotting for F1 is furnished in Fig. 7.7. β and α of other BEs are also calculated similarly and tabulated in Table 7.13.

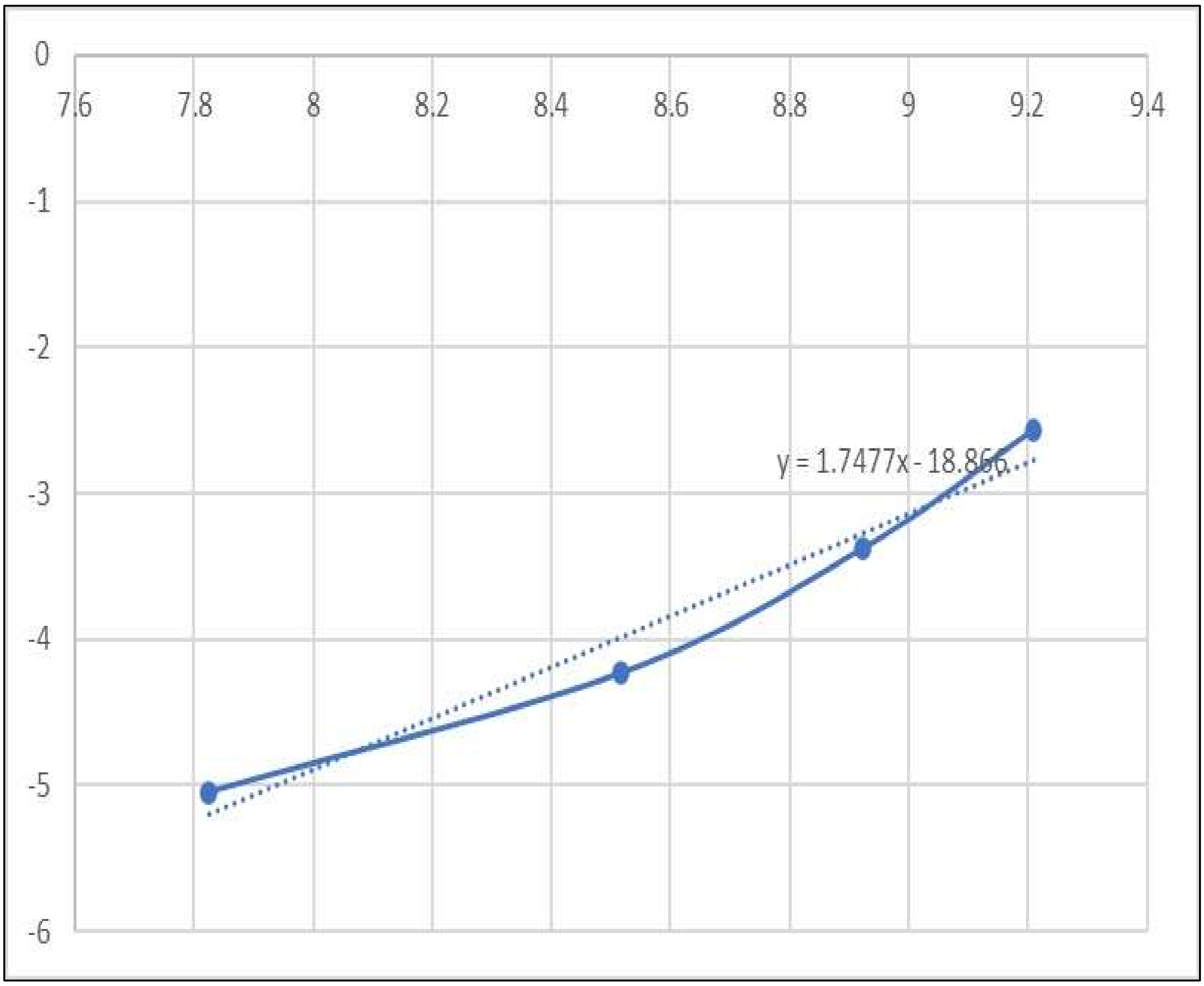

Fig 7.7 Weibull distribution plotting for F1

BEs	Shape Parameter (β)	Scale Parameter (α)	R Square	R Square (Adjusted)
F1	1.7477	48764.54671	96.02%	94.04%
F2	1.7155	48215.94525	98.02%	97.03%
F3	1.7672	64400.94963	96.52%	94.78%
F4	2.149	90131.72178	99.59%	99.38%
F5	1.7672	64400.94963	96.52%	94.78%
F6	2.2084	30447.64137	94.56%	91.83%
F7	1.6252	99766.05886	98.96%	98.45%
F8	3.3525	65684.44705	98.08%	97.13%
F9	2.632	81450.50058	97.21%	95.82%
F10	2.5124	95030.07831	98.94%	98.41%
F11	1.6392	266380.0575	98.86%	98.29%
F12	2.2706	111381.552	91.85%	87.78%
F13	1.8538	167601.6193	96.96%	95.44%
F14	0.9662	2393985.949	99.90%	99.85%
F15	4.16	94353.88178	98.92%	98.37%
F16	4.16	94353.88178	98.92%	98.37%

Table 7.13 β, α values along with R-squared and Adjusted R-squared values of BEs

The values of R and λ have been computed using equations 7.13 and 7.14. Period-wise values of R and λ for all BEs are arranged in Tables 7.14 and 7.15, respectively. The reference calculation for evaluating R and λ under the time span of 2500 Hours is described for F1.

$$R(t) = exp^{\left[-\left(\frac{2500}{48764.54671}\right)^{1.7477}\right]} = 0.994454088$$

$$\lambda = \frac{1.7477 * 2500^{(1.7477-1)}}{48764.54671^{1.7477}} = 6.5281 * 10^{-6}$$

BEs	Reliability (R)			
	2500 Hours	5000 Hours	7500 hours	10000 Hours
F1	0.994454088	0.981497049	0.96277512	0.939207194
F2	0.993779887	0.979717224	0.95975021	0.934918841
F3	0.996794704	0.989131377	0.97787493	0.963484852
F4	0.999549139	0.998001886	0.99523089	0.991168326
F5	0.996794704	0.989131377	0.97787493	0.963484852
F6	0.996003668	0.981663645	0.95570004	0.918025306
F7	0.997502863	0.992316742	0.98520314	0.976487612
F8	0.99998258	0.999822084	0.99930745	0.998184224
F9	0.999895796	0.999354232	0.99812379	0.996003697
F10	0.999892704	0.999387958	0.99830583	0.996512907
F11	0.999525411	0.99852243	0.99712992	0.995404658
F12	0.999819686	0.999130243	0.99781754	0.995810189
F13	0.999588618	0.998513857	0.99685126	0.994638747
F14	0.998683877	0.997430321	0.99620029	0.9949858
F15	0.999999724	0.999995072	0.99997338	0.999911899
F16	0.999999724	0.999995072	0.99997338	0.999911899

Table 7.14 Period-wise values of R

BEs	Hazard Rate (λ) in (Failure/Hour)			
	2500 Hours	**5000 Hours**	**7500 hours**	**10000 Hours**
F1	3.88783E-06	6.5281E-06	8.83996E-06	1.09614E-05
F2	4.28157E-06	7.03056E-06	9.39687E-06	1.15446E-05
F3	2.2694E-06	3.86243E-06	5.27179E-06	6.57372E-06
F4	3.87648E-07	8.59648E-07	1.36978E-06	1.90636E-06
F5	2.2694E-06	3.86243E-06	5.27179E-06	6.57372E-06
F6	3.53727E-06	8.17397E-06	1.3342E-05	1.88885E-05
F7	1.62537E-06	2.50701E-06	3.23034E-06	3.86687E-06
F8	2.33604E-08	1.19303E-07	3.09676E-07	6.09292E-07
F9	1.09711E-07	3.40042E-07	6.59043E-07	1.05393E-06
F10	1.07834E-07	3.07633E-07	5.68006E-07	8.77628E-07
F11	3.11252E-07	4.84765E-07	6.28187E-07	7.55005E-07
F12	1.63783E-07	3.95146E-07	6.61453E-07	9.53337E-07
F13	3.0511E-07	5.51412E-07	7.79513E-07	9.96543E-07
F14	5.0899E-07	4.97204E-07	4.90436E-07	4.85691E-07
F15	4.58757E-10	4.10051E-09	1.47668E-08	3.66516E-08
F16	4.58757E-10	4.10051E-09	1.47668E-08	3.66516E-08

Table 7.15 Period-wise values of λ

7.3.3 RCM and its consequences

System reliability (R_{sys}) and system hazard rate (λ_{sys}) have been evaluated from respective equations 7.15 to 7.18, utilizing the values of Tables 7.14 and 7.15. Readers may go through the concept of reliability evaluation for series and parallel systems in this regard. Periodical values of R_{sys} and λ_{sys} are reflected in Table 7.16 and their periodical distribution curve as shown in Fig. 7.8 and 7.9, respectively.

Time (Hours)	**R_{sys}**	**λ_{sys} (per hour)**
2500	0.988228409	2.00691E-05
5000	0.961098764	3.37697E-05
7500	0.921916181	4.63204E-05
10000	0.872324394	5.93621E-05

Table 7.16 Periodical values of R_{sys} and λ_{sys}

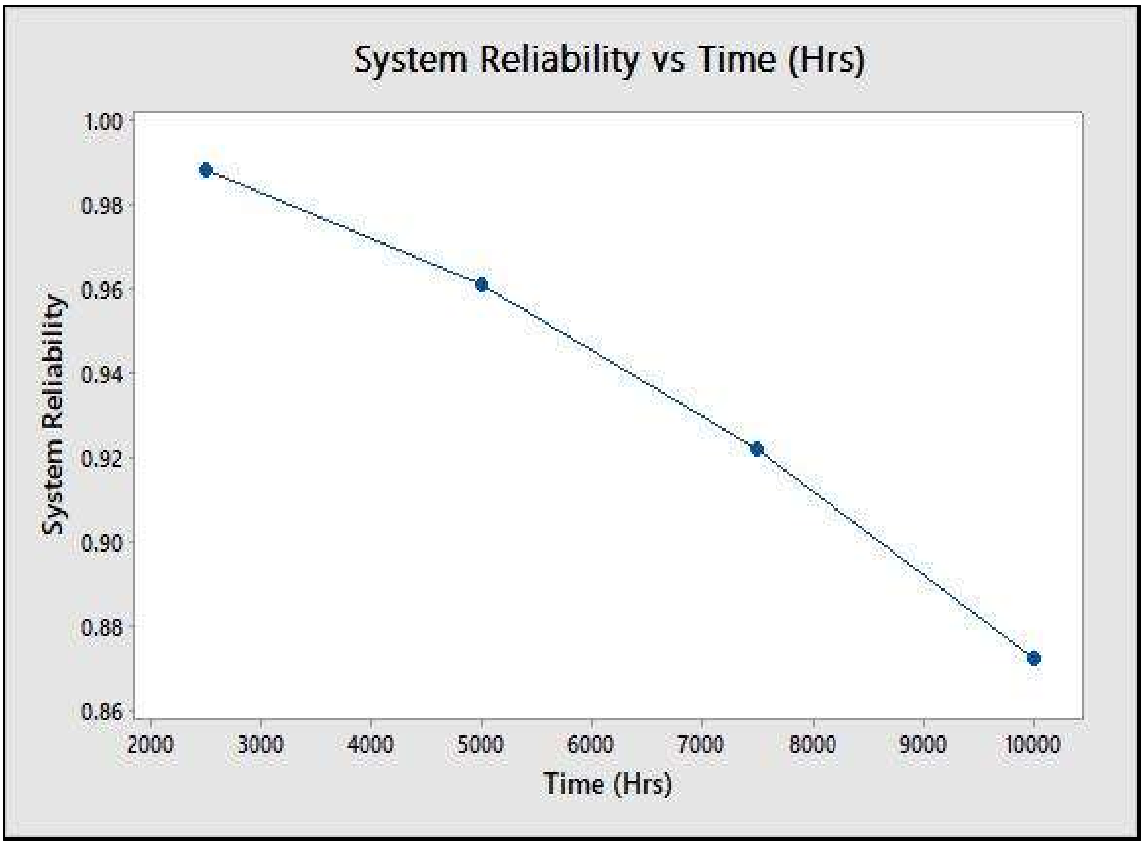

Fig 7.8 Periodical distribution curve of R_{sys}

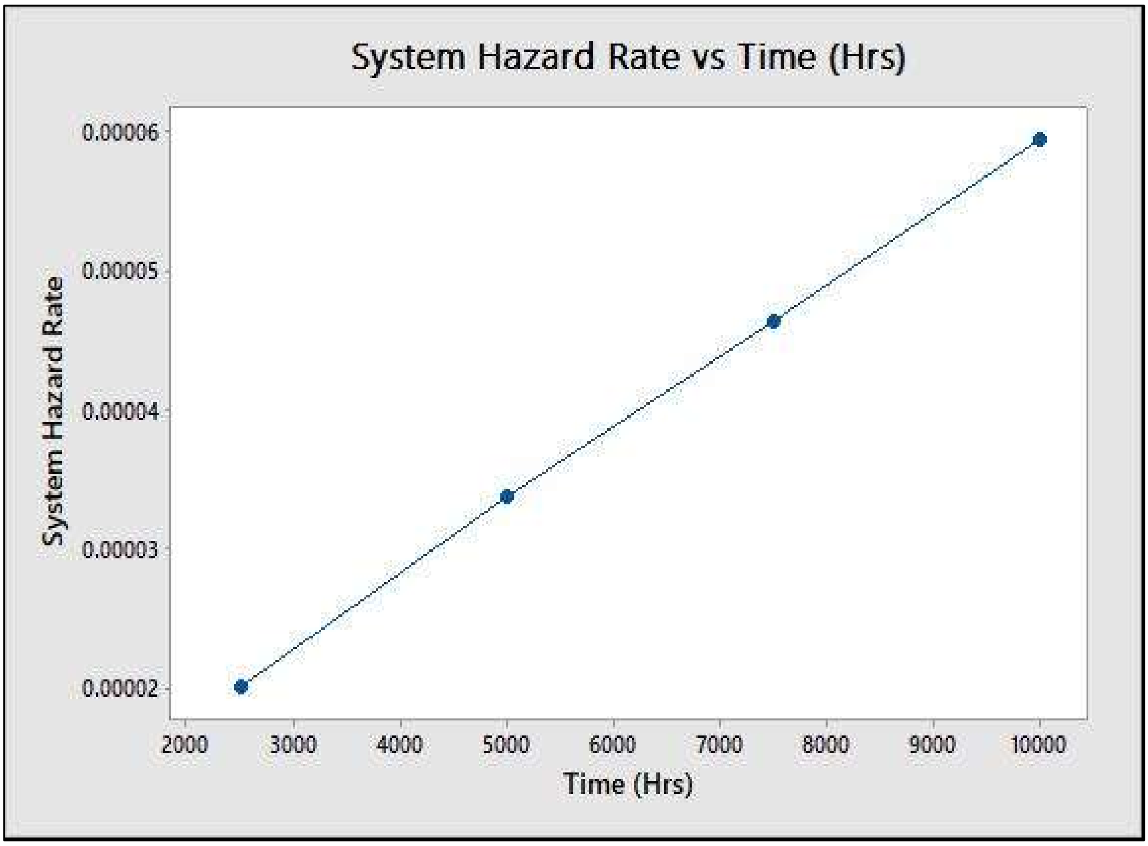

Fig 7.9 Periodical distribution curve of λ_{sys}

A threshold value of system reliability, R_{th}, which is the minimum operating criterion of the system, has been chosen as 0.9. While tracing the R_{sys} vs Time graph as shown in Fig.7.8 it is found that R_{sys} is reaching R_{th} approximately at 8610 hours. Among all the BEs, the hazard rate value of event F6 was found maximum with a value of 1.57636×10^{-05}/hr. at that instant. After replacing the prime constituent responsible for F6, i.e. 12-volt power source, the value of R_{sys} shifted to 0.902. This minute change is due to the parallel configuration of data transfer between the ground station and printer. The R_{sys} approaches R_{th} for the second time approximately at 8720 Hours. The hazard rate of event F2 has a maximum value of 1.04669×10^{-05}/hr. on that period. Adopting the previous maintenance strategy for said BE, the R_{sys} improved from 0.9 to 0.9499. Table 7.17 displays the effect of replacement on R_{sys}. Fig. 7.10 emphasizes on improvement of R_{sys} due to the adaptation of the replacement strategy to make the system sustainable.

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Time (Hrs.)	System Reliability Before Replacement	System Reliability after Replacement action corresponding to F6	System Reliability after Replacement action corresponding to F2
2500	0.988228409	**	**
5000	0.961098764	**	**
7500	0.921916181	**	**
8610	0.901098936	0.902852737	**
8720	0.898928935	0.900766325	0.949988276
10000	0.872324394	0.875300215	0.934380433

Table 7.17 Effect of replacement of components on R_{sys}

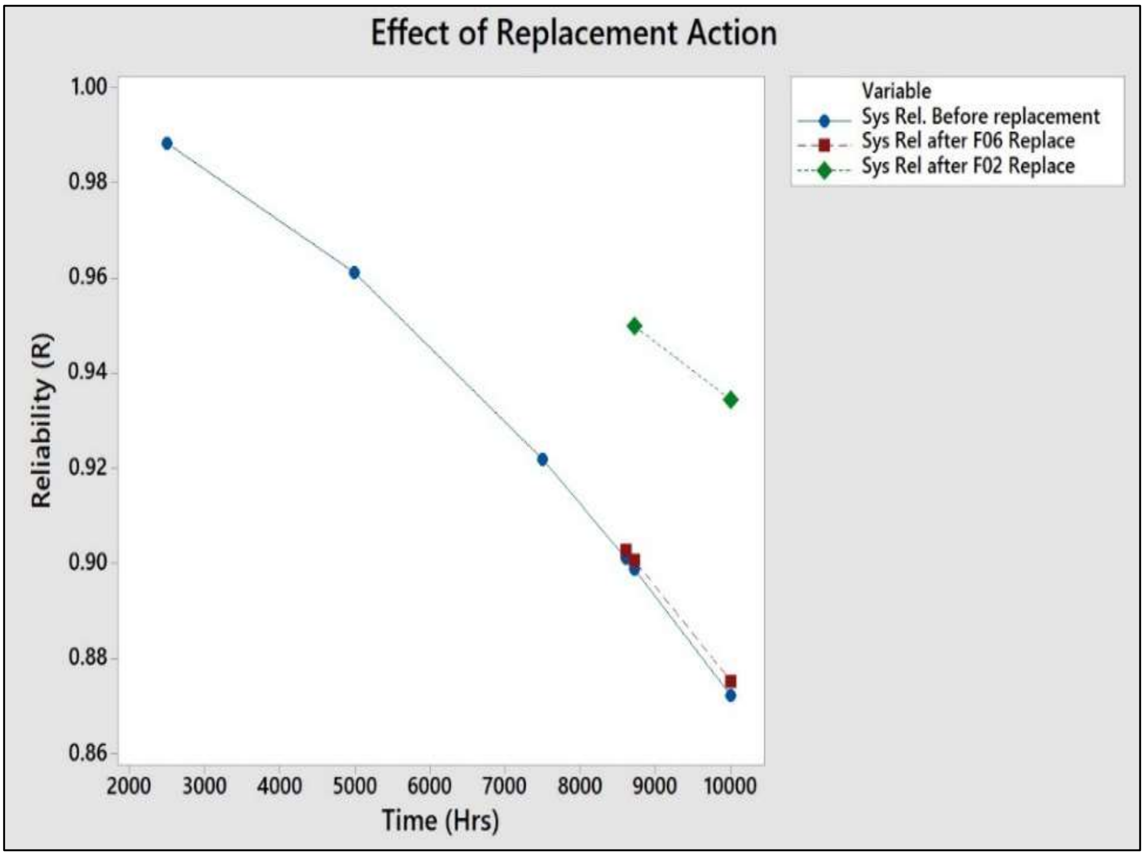

Fig. 7.10 Effect of R_{sys} due to replacement strategy

Chapter 8

Diagnosis and prognosis of an IoT-based WDCS using BN-ARIMA combined Model

8.1 Introduction

IoT, as discussed elaborately in the previous chapter, is an integration of software, hardware, and network connectivity through which communications have been set up between different components (Gokhale et al. 2018). It has a vast application in different domains along with some challenges (Khanna et al. 2020). Under these circumstances, an equitable maintenance policy is essential for any system or equipment for easy operation. Diagnostics and Prognostics are the two prime techniques associated with maintenance. Diagnostics are associated with the detection and isolation of system failures, whereas prognostics are the technique of futuristic prediction of the system based on present and historical conditions (Ly et al. 2009). Adequate maintenance is useful for smooth operation and enhancement of the service life of the system. Probable faults leading to system failure have to be identified to do so. Fault tree analysis (FTA) has been considered as a valuable tool in this regard (Srinath, 1991), as discussed in Chapter 7. The concept of FFTA, i.e. Fuzzy fault tree analysis, has also been discussed with a case study on an IoT-based device. However, in the case of a fuzzy set, the value of the membership degree for a certain event is bounded between 0 to 1, which also implies that the non-membership degree of the said event is the complement of the membership degree. But in reality, the value of the non-membership degree might not be the complement of the membership degree due to the presence of some hesitation degree. To deal with such a phenomenon, the concept of the Intuitionistic Fuzzy set (IFS) has been revealed by Atanassov (1986), where the hesitation margin, along with the membership and non-membership degree, has been incorporated. Pythagorean fuzzy set (PFS) (Yager, 2013) and Fermatean fuzzy set (FFS) (Senapati et al. 2020) are the prime upgradations of IFS, where a larger size of nonstandard membership grades has been corroborated. A clear superiority of FFS over the PFS has been established by Senapati et al. (2020) and Simić et al. (2022) due to its greater nonstandard membership grades. Due to such superior features, the FFS has been considered for this research work. The amalgamation between FTA and FFS has set up a new tool, namely, Fermatean-Fuzzy fault tree analysis (FFFTA), which has been found as a Novel approach for the evaluation of failure probabilities (FP) of the Basic Events (BEs) of an IoT-based intelligent weight data communication system as described below. A Bayesian Network (BN) based fault diagnosis approach (Cai et al. 2017) has been applied in this study to observe fault symptoms based on logical reasoning. It is useful to identify the most vulnerable BE that might be responsible for system failure. The identification process takes place based on the values of Posterior Probability (PP) and Sensitivity (S) of the BEs. After the identification, a prognostic model has been developed to predict the Remaining useful life (RUL) of the basic events. Under this section, the Autoregressive Integrated Moving Average (ARIMA) time series model (Lu et al.,2020) has been utilized to set up an RUL predicting equation. During the study, it was found that the FP of all the BEs has fulfilled the Pareto principle during the entire observation at different periods. The similar system that has been considered for the case study in Chapter 6 is used here. Therefore, no further illustration of the system has been given. The important theoretical concepts of the chapter have been discussed in the next section.

8.1.1 FFFTA and its Novelty

The idea of FFFTA is situated on two pillars: Fermatean Fuzzy set theory (FFS) and Fault tree analysis (FTA). First preference has been given to FTA, based on which a fuzzy approach has been applied. The term "tree" indicates the logic diagram's shape, consisting of nodes and branches (Srinath,1991). It is a top-down approach that has gone through a series of logic gates up to component failure stages known as the Basic events. This tool is extensively used to compute the probability of system failure by identifying the failure probability of the basic events. Both quantitative and qualitative assessments can be performed to pinpoint system failure. The causes of system failure are analysed and gradually split into hierarchical levels until the effect of component failure can be identified. In this study, this method has been adopted for different periods. Based on the following results, the degradation percentage of each BE has been calculated. The authors have constructed a time series plot using intermediate random data generation in ascending order based on the expert's view.

On the other hand, the fuzzy set theory (Zadeh, 1965) is an efficient tool for pulling out real data from numerous vague data. This method could be adopted in two situations (Ross, 2009), as stated in the previous chapter. Fuzzy probability is an inexact form of a real number. The weight of imprecision is known as the membership function, which varies from 0 to 1. A fuzzy number represents itself in the probability space under a fuzzy set with a value ranging from 0 to 1. There are various Fuzzy numbers (Nasir et al. 2021) that different researchers have used. In this study, a triangular fuzzy number has been used. To identify the characteristics of the vagueness of an element more clearly under a probability space, Atanassov (1986) has introduced the concept of IFS, where both the Membership function and the non-membership function have been included in the set for evaluation purposes. Under this concept, the weight of imprecision has been elicited with both the degree of membership (μ) and the degree of non-membership (ν) under the probability space, with the condition:

$$0 \leq \mu + \nu \leq 1 \tag{8.1}$$

And

$$\pi = 1 - (\mu + \nu) \tag{8.2}$$

Where π is known as the degree of non-determinacy of the set.

There are numerous applications of IFS in various fields, including decision-making, Reliability assessment, Fault tree analysis, etc. To enlarge the weight of the imprecision of the membership grade and non-membership grade, Senapati et al. (2020) proposed the concept of the Fermatean fuzzy set (FFS) approach, as mentioned before. Like IFS, both the degree of membership (μ) and the degree of non-membership (ν) have been assigned for an element under a probability space with a condition:

$$0 \leq \mu^3 + \nu^3 \leq 1 \tag{8.3}$$

And

$$\pi = \sqrt[3]{1 - \mu^3 - \nu^3} \tag{8.4}$$

Where π is known as the degree of non-determinacy of the set.

The triangular fuzzy number (TFN) has been considered for this study due to its simplicity (Herrera et al. 2005). An extended elaboration regarding the Fermatean Triangular fuzzy number (FTFN) has been presented by Akram et al. (2023). Based on the observation, the membership function and non-membership function have been portrayed in Fig. 8.1, and the same are expressed in Equations 8.5 and 8.6, respectively.

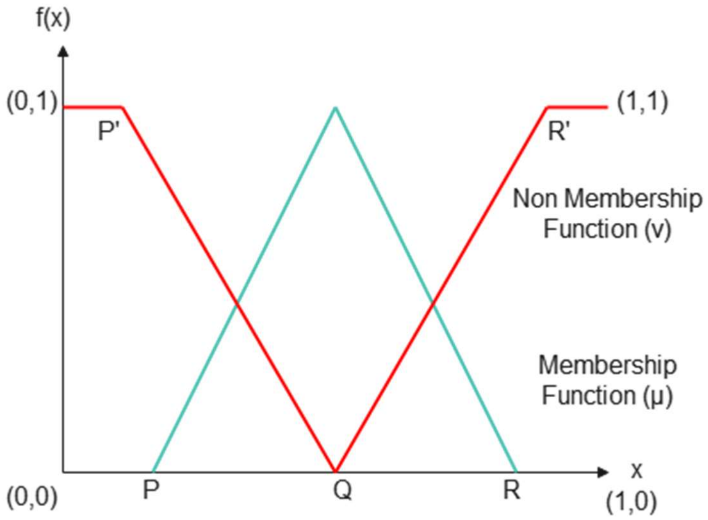

Fig 8.1 Membership function and non-membership function of FTFN

$$\mu(x) = \begin{cases} \frac{x-P}{Q-P}, & P \le x < Q \\ 1, & x = Q \\ \frac{R-x}{R-Q}, & Q < x \le R \\ 0, & otherwise \end{cases} \tag{8.5}$$

$$\nu(x) = \begin{cases} \frac{Q-x}{Q-P'}, & P' \le x < Q \\ 0, & x = Q \\ \frac{x-Q}{R'-Q}, & Q < x \le R' \\ 1, & otherwise \end{cases} \tag{8.6}$$

After the demonstration of both the Membership function and non-membership function using FTFN, the necessary task of the research work is to enumerate the degree of Membership and Non-membership from both the FTFN, respectively. The idea of such a task has been provided by Nayagam et al. (2008). The insights of the said study provide a thorough knowledge of the calculation of the scores of a TFN, and the basic architecture has been depicted in Fig. 8.2. The significance of the scores is observed in the figure. According to the figure, the terms M and N indicate the TFN of Membership and non-membership functions, respectively. Similarly, the terms L(M) and R(M) are the left score and right score of M, respectively, and are presented in Equations 8.7 and 8.8, respectively. On the other hand, NL(M) and NR(M) are the new left score and the new right score of M, respectively, and both of them are elaborated in equations 8.9 and 8.10.

$$L(M) = \frac{1-P}{1+Q-P} \tag{8.7}$$

$$R(M) = \frac{R}{1+R-Q} \tag{8.8}$$

$$NL(M) = \frac{P}{1+P-Q} \tag{8.9}$$

$$NR(M) = \frac{1-R}{1+Q-R} \tag{8.10}$$

Based on the above formulas, the Membership score of M {T(M)} and the new membership score of M {NT(M)} have been evaluated using equations 8.11 and 8.12, respectively.

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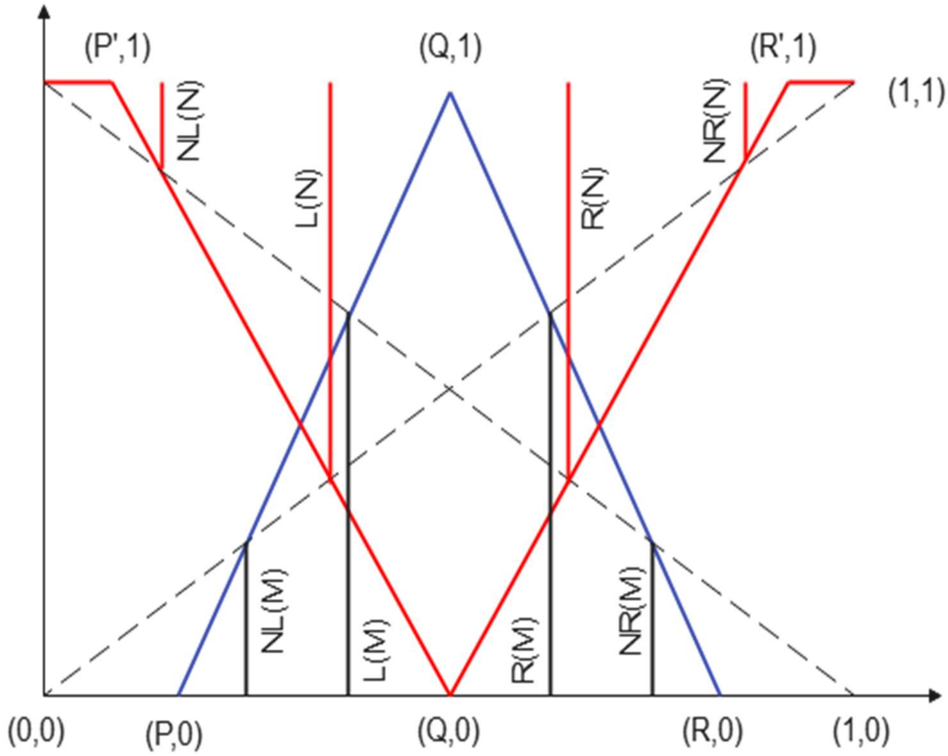

Fig 8.2 Different scores of TFN

$$T(M) = \frac{1+R(M)-L(M)}{2} \quad (8.11)$$

$$NT(M) = \frac{1+NL(M)-NR(M)}{2} \quad (8.12)$$

As the TFN M and TFN N are located exactly in opposite directions, the complement values of the legs have to be considered for the evaluation of the non-membership score. So, to derive the non-membership score of said TFN, the values of the $L_c(N)$, $R_c(N)$, $NL_c(N)$, and $NR_c(N)$ have been calculated. Based on the values, the non-membership score of N, $T_C(N)$, and the new non-membership score of N, $NT_c(N)$ have been derived using Equations 8.13 and 8.14.

$$T_C(N) = \frac{1+R_C(N)-L_C(N)}{2} \quad (8.13)$$

$$NT_C(N) = \frac{1+NL_C(N)-NR_C(N)}{2} \quad (8.14)$$

Based on the assumptions made by Nayagam et al. (2008), the membership and non-membership score of FTFN can be represented as {T(M), $NT_c(N)$}. The scores of the TFN must satisfy Equation 8.3 to be considered for the FFS approach. A list of TFN and their linguistic representation for the said problem is displayed in Table 8.1. A fuzzy set with seven linguistic expressions has been selected (**Source:** Chen et al. 2008), based on which the linguistic terms have been decoded. The respective scores of the said TFN have also been included in the table. By applying those scores to Equation 8.3, it has also been confirmed that all the TFNs have satisfied the criterion for the FFS approach.

Among the seven TFNs, it is observed that all of them have satisfied the condition for FFS. However, it has also been seen that the last four of them have not satisfied the criterion for IFS. This also concluded that FFS provides higher nonstandard membership grades compared to IFS. The integration of the FFS approach into the FTA has been found useful in decoding the obscure data provided by the experts regarding the health condition of basic events in terms of linguistic values. By decoding the values using FFFTA, the present parameters of the system have been evaluated.

8.1.2 Fault diagnosis

The term Diagnosis, in a general way, can be described as "The art or act of identifying a disease from its signs and symptoms". In engineering terms, it can be described as the identification and isolation of faults and failures. It also decides the impact of faults on system health. The term fault diagnosis is inextricably linked with condition monitoring. Condition monitoring technique inspects the operation parameter to provide a prior indication of a fault. On the other hand, fault diagnosis detects and identifies the fault (Gao et al. 2021). Combining both techniques, proper repair strategies are taken before the system failure occurs. There are various methods available for fault diagnosis (Van Tung et al. 2009), i.e., Model-Based Approach, Knowledge-based Approach, and Pattern Recognition Approach. Knowledge-based diagnosis approach is also known as the data-driven approach, which has been found more effective by many researchers due to the involvement of real-time data. The Bayesian Network (BN) model comes under the data-driven approach for fault diagnosis, which is a very effective tool in this regard. BN is an integrated model that is combined with probabilistic network theory and graph theory, which illustrates a set of random variables and their conditional dependence through a directed acyclic graph. Construction of BN based on the model structure and the BN evaluation structure. The first one is defined as an acyclic probability structure in which nodes are represented by variables and the relationship between variables is shown by directional arrows. Parent nodes indicate the basic events from which direction arrows have been generated, and child nodes are the top event in which the arrows have been merged. The BN evaluation structure quantifies the relationship between nodes and parents through a conditional probabilistic table (CPT) based on the chain rule. The CPT holds the information regarding the possible value of variables associated with a node with respect to all conditional probabilities for all combinations of values of variables associated with the parent node. It has extensive use in reliability analysis, causal analysis, fault diagnosis, etc. Due to its versatile acceptance, this method has been adopted in this work.

FTFN Identification with Linguistic Representation	Membership TFN			Non-Membership TFN			L(M)	R(M)	Membership score T(M)	NLc(N)	NRc(N)	Non-Membership Score NTc(N)	Validation check of IFS Condition based on Equation 1	Validation check of FFS Condition based on Equation 3
Negligible (N)	0	0	0.13	0	0	0.19	1	0.115	0.057522124	1	0.31933	0.84033613	0.89785826	0.5936061
Quite Low (QL)	0	0.17	0.29	0	0.17	0.37	0.8496	0.2589	0.204685525	1	0.475	0.7625	0.96718552	0.4518978
Low (L)	0.2	0.33	0.46	0.13	0.33	0.54	0.7105	0.4071	0.348276665	0.89167	0.61983	0.63591598	0.98419264	0.2994023
Medium (M)	0.4	0.5	0.63	0.29	0.5	0.71	0.5575	0.5575	0.5	0.76033	0.76033	0.5	1	0.25
High (H)	0.5	0.67	0.79	0.46	0.67	0.87	0.4071	0.7054	0.649138748	0.61983	0.89167	0.36408402	1.01322277	0.3217968
Quite High (QH)	0.7	0.83	0.96	0.63	0.83	1	0.2589	0.8496	0.795314475	0.475	1	0.2375	1.03281448	0.5164529
Severe (S)	0.9	1	1	0.79	1	1	0.115	1	0.942477876	0.34711	1	0.17355372	1.1160316	0.8423973

Table 8.1 Detailed representation of TFN along with scores

8.1.3 Failure Prognosis

Prognosis is the method of prediction of a future state based on present and past conditions, along with an estimation of the remaining useful life (RUL) of the component. RUL is defined as the time left before a failure occurs. The health condition of a system can be identified with the help of fault diagnosis and condition monitoring. Deterioration patterns can be identified, and based on that pattern, a prognostic approach is used to identify possible periods of failure and RUL. The concept of prognosis has been shown using an Iceberg model diagram as shown in Fig. 8.3. There are three kinds of prognostic approaches, namely the statistical approach,

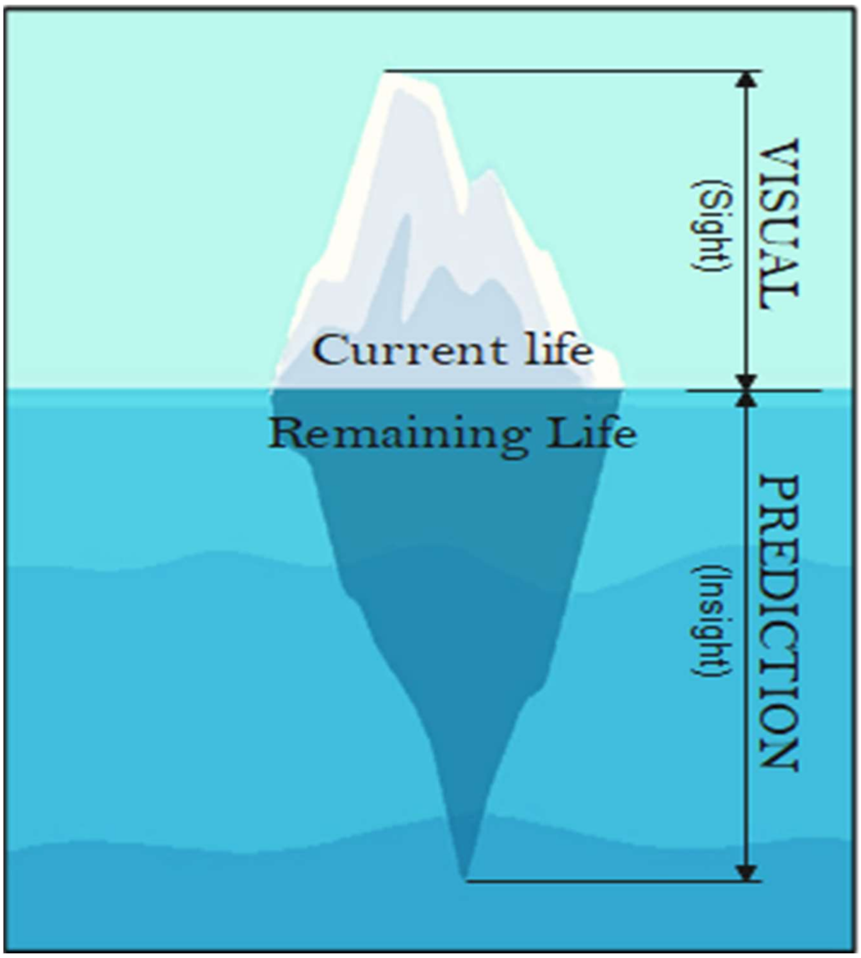

Fig. 8.3 Iceberg model describing Diagnosis and Prognosis

Model-based approach and data-driven approach. The details of such an approach have been discussed by van Tung et al. (2009). So, prognosis is deeply associated with Health management (Duong et al.,2018). The basic requirement of the prognostic algorithm is to consider a different kind of workload and reduce it to a single value. Based on the theories and literature review, a general comparison between Fault Diagnosis and Failure Prognosis can be established, as shown in Table 8.2. Also, A combined framework of Diagnosis and Prognosis is shown in Fig. 8.4.

Characteristics	Fault Diagnosis	Failure Prognosis
Definition	A technical term for the detection and isolation of a fault based on severity.	A scientific prediction of the likely development of the fault and RUL of the faulty system.
Basis	Condition Monitoring and Identification of potential causes of fault.	Present and past condition of the system.
Time frame	Concern about the current condition of the system	Concern about the future development of the system's condition

Table 8.2 Comparison between Fault Diagnosis and Failure Prognosis

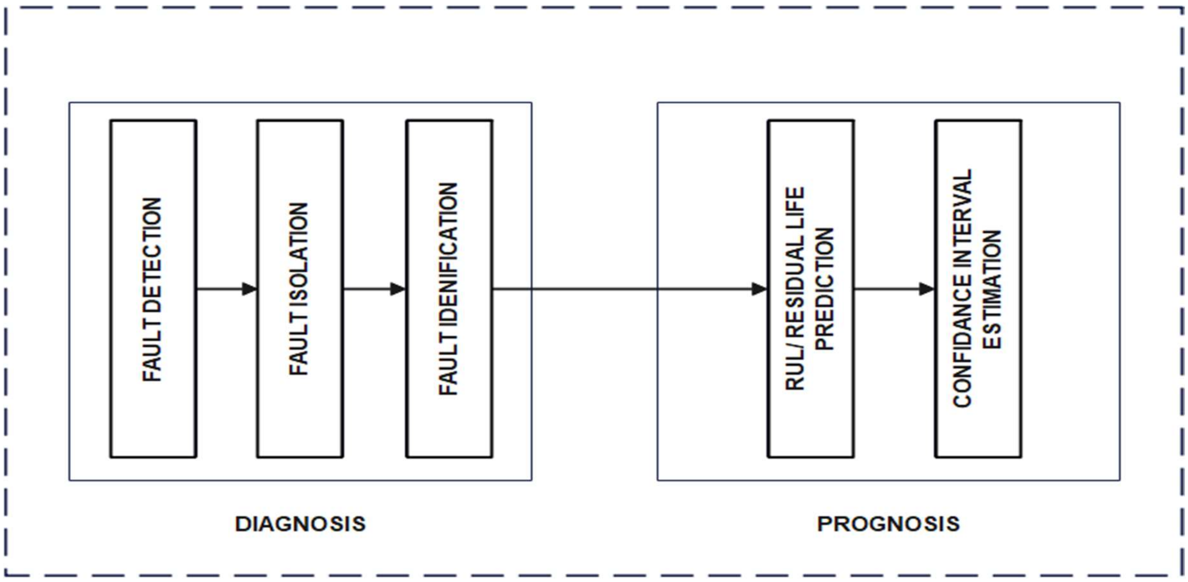

Fig. 8.4 Combined Framework of Diagnosis and Prognosis

8.2 Methods and materials

The prime aspects of the research work are to identify the critical BEs of the intelligent system and their RUL prediction. To fulfil the mission, this work has been carried out in three phases. Firstly, FFTA has been conducted based on experts' elicitation to find out the FP of all the BEs. In the second phase, BN has been developed using the results of the FFTA. By mapping on BN, the posterior probability has been calculated. This is also called a diagnosis impact factor. Studying those values, one can identify which BEs are most responsible for system failure. After identifying the most critical BE, the third phase has been carried out by developing an equation for RUL prediction using the ARIMA model. A roadmap of the research work has been shown using a basic flow chart (Fig. 8.5). The detailed Methodology of the research work has been discussed with necessary formulae and notations.

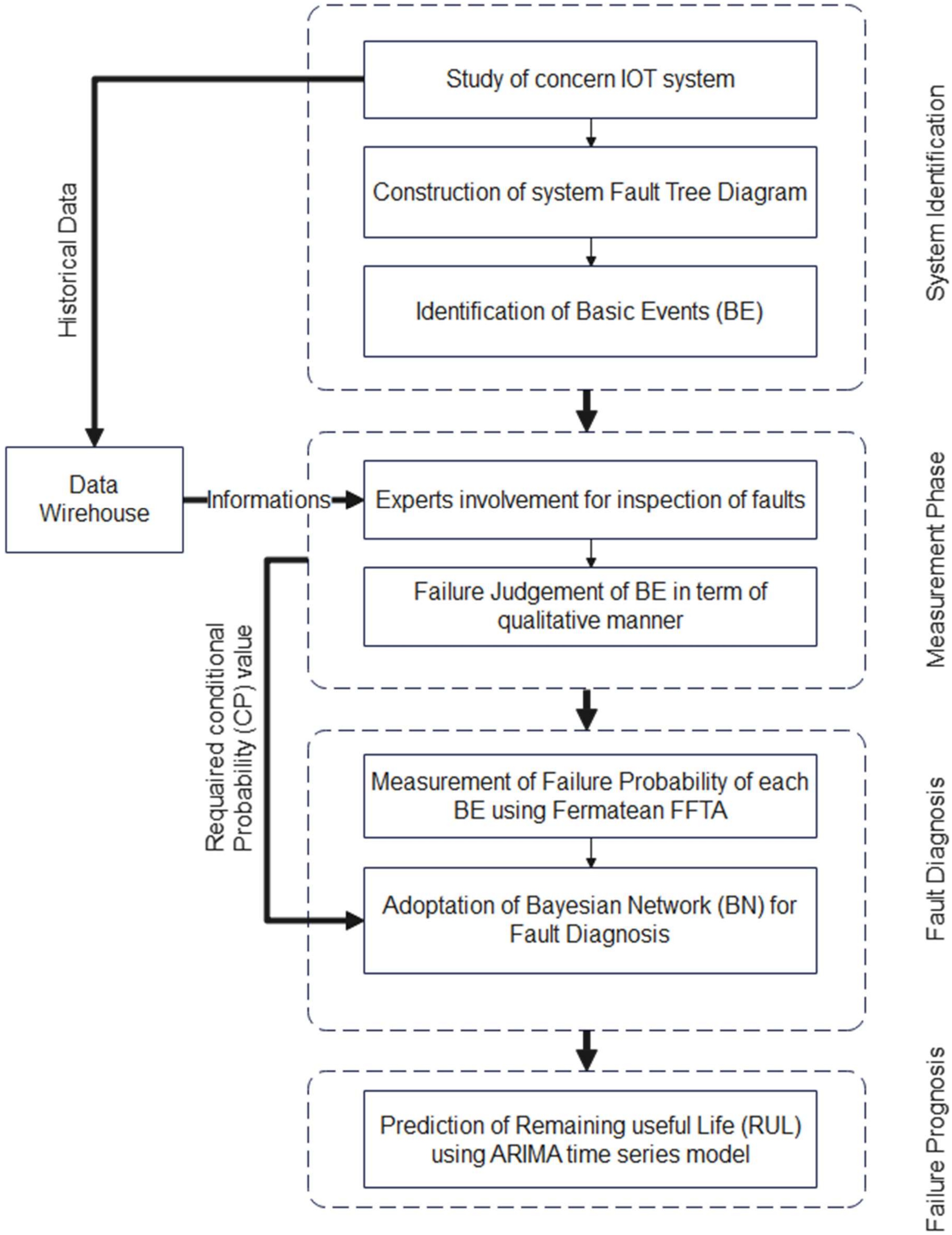

Fig. 8.5 Roadmap of the research work

8.2.1 Adaptation of FFFTA for failure probability evaluation

Before conducting the analysis, we have perceived the system to be analyzed. Based on overall knowledge, the fault tree of the system has been constructed, considering all possible failures in mind. The FT diagram of the system has already been shown in the previous chapter, i.e. Chapter 7, Fig. 7.4. Hence, the same has been considered for the upcoming analysis. To carry out the following research work, 3 experts have been engaged for their valuable opinion regarding system and sub-system failures. The rating details of the experts are presented in Table 8.3. The experts and their assigned scores have been reflected in Table 8.4. Based on the assigned scores, the sum assigned scores of all experts has been evaluated. Based on available data, the weightage value of each expert has been expressed in Table 8.5. The BEs have been identified using FTA and numbered accordingly. A brief description of the BEs, along with Period-wise linguistic representation of the experts, is noted down in Table 8.6.

Sl. No.	Particulars	Category	Score
		HOD / Senior Managers	4
		Deputy Managers / Assistant Managers	3
1.	Post Held	Supervisors / Junior Engineers	2
		Technicians / Skill Workers	1
		Over 25 Years	4
2.	Experience	More than 15 Years & less than 25 Years	3
		More than 5 Years & less than 15 Years	2
		Below 5 years	1
		M.E/M. Tech/M.B.A. and Above	4
3.	Academic Merit	B.E/B. Tech	3
		Diploma Engineering	2
		I.T.I/ 12th Standard	1
		More than 40	4
4.	Field Involvement	More than 25 & less than 40	3
	(In Hours per Week)	More than 10 & less than 25	2
		Less than 10	1

Table 8.3 Rating of experts based on particulars

Expert (E)	Designation	Job/Research Experience	Qualification	Time of involvement with the Job-shop activity	Assign Score (x_i)
E1	Senior Manager (Production) (Score: 4)	27 Years (Score: 4)	M.B.A (Score: 4)	7 Hours/ Week (Score: 1)	13
E2	Assistant Manager (Production Planning Control) (Score: 3)	7 Years (Score: 2)	M. Tech (Score: 4)	15 Hours/Week (Score: 2)	11
E3	Supervisor (Smelting Plant) (Score: 2)	16 Years (Score: 3)	Diploma Engineering (Score: 2)	36 Hours/ Week (Score: 3)	10
	The sum of the assigned score ($\sum x_i$)				**34**

Table 8.4 Details of experts along with assigned score

The calculated weightage value of each expert is shown below. The data has been adopted from Table 8.4.

Expert (E)	E1	E2	E3
Weightage $\left(\frac{x_i}{\sum x_i}\right)$	0.382353	0.323529	0.294118

Table 8.5 Calculated Weightage of Experts

After decoding the linguistic values of BEs given by the experts, the FFFTA has been carried out to evaluate the FP of each BE. The steps have been imposed on both the TFN of the Membership function and the non-membership function, respectively. For a smooth experiment, Table 8.6 provides a vast periodic failure data for all the subsystems of the IoT system. It should be noted that the data are vague in nature and given by the experts based on past observations. Hence, the final results might not be the exact value but close to the exact one. The detailed Table has been presented on the next page due to a lack of space. The failure of the basic events is represented as “F” followed by the number of the BE.

Failure	Basic Events (BEs)	Period-wise linguistic representation of the experts											
		2500 Hours			5000 Hours			7500 Hours			10000 Hours		
		Exp. 1	Exp. 2	Exp. 3	Exp. 1	Exp. 2	Exp. 3	Exp. 1	Exp. 2	Exp. 3	Exp. 1	Exp. 2	Exp. 3
F01	Weight sensor failure	M	M	H	H	H	QH	QH	H	S	QH	QH	S
F02	Weight processor failure	H	H	H	QH	H	QH	QH	QH	QH	S	QH	QH
F03	Current loop Converter failure	M	M	M	H	H	H	H	QH	QH	QH	QH	QH
F04	Display Failure	L	L	M	M	M	M	H	M	M	H	H	H
F05	Current loop Converter 2 failure	M	M	M	H	H	H	QH	H	QH	S	QH	QH
F06	12-volt power sources failure	M	H	H	H	H	QH	QH	QH	S	S	S	S
F07	25-pin serial converters to USB converter failure	L	M	M	M	H	H	H	QH	QH	QH	QH	QH
F08	Raspberry Pi power input failure	N	QL	N	N	QL	QL	QL	QL	QL	L	QL	L
F09	Inbuilt Wi-Fi chip failure	QL	QL	QL	QL	L	QL	L	L	L	M	M	M
F10	Ground station power failure	QL	N	N	QL	QL	QL	L	QL	L	M	L	L
F11	Backup crane malfunction	L	L	QL	L	L	L	L	M	L	M	M	L
F12	Ground station Wi-Fi receiver failure	QL	QL	QL	L	L	L	M	M	M	M	H	M
F13	Backup crane Wi-Fi receiver failure	QL	L	L	L	L	M	L	M	M	M	M	M
F14	Software failure due to a malware attack	QL	QL	L	L	L	L	M	L	L	M	M	M
F15	Technical Failure from M-to-M config	N	N	N	N	N	QL	N	QL	QL	QL	QL	QL
F16	Technical Failure from M to S config	N	N	N	N	N	N	N	QL	N	N	QL	N

Table 8.6 Description and Linguistic Representation of BEs

After decoding the linguistic values of BEs given by the experts, the FFFTA has been carried out to evaluate the FP of each BE. The steps have been imposed on both the TFN of the Membership function and the non-membership function, respectively.

8.2.2 Aggregation of BEs

The said part has already been discussed in the previous chapter. Hence, the same approach has been followed in this portion. Equations 7.2 to 7.6 have been used for the Aggregation of BEs. Though the values are different due to different judgments given by the experts in different chapters, the calculations are the same. Based on the result obtained in this part, the defuzzification has been carried out, which is discussed in the next section.

8.2.3 Defuzzification and computation of FP

Under this step, the fuzzy values have been transferred into corresponding crisp values, X'. To do so, the concept provided by Akram et al. (2023) has been adopted. According to the formulae provided in the article and reference to Fig. 8.2, the crisp values corresponding to R_{AG} {(P, Q, R), (P', Q, R')} have been expressed as:

$$X' = \frac{\{(P+4Q+R)+(P'+4Q+R')\}}{12} \tag{8.15}$$

Badida et al. (2019) have calculated the FP using the crisp value obtained in equation 7.15. Based on their work, the FP has been evaluated considering the following equations:

$$k = [(\frac{1}{X'} - 1)^{\frac{1}{3}}] \times 2.301 \tag{8.16}$$

$$FP = \frac{1}{10^k} \tag{8.17}$$

The value of FP has been considered as a prior probability while mapping the FT on the BN. It indicates the importance of FP from the BN point of view. The construction and evaluation of posterior probability have been discussed in the next step.

8.2.4 Mapping into a Bayesian Network for fault diagnosis

After obtaining the results of the FP of BEs using FFTA, a question may come to mind: What are the effects of each BE on the entire system failure? Based on the FP values of BEs, the FP of the system has been evaluated. To identify the dominance of BEs on system failure, the FT of the system has been mapped into the Bayesian network. Chiremsel et al. (2016) have provided a pictorial view of the mapping process as shown in Fig. 8.6.

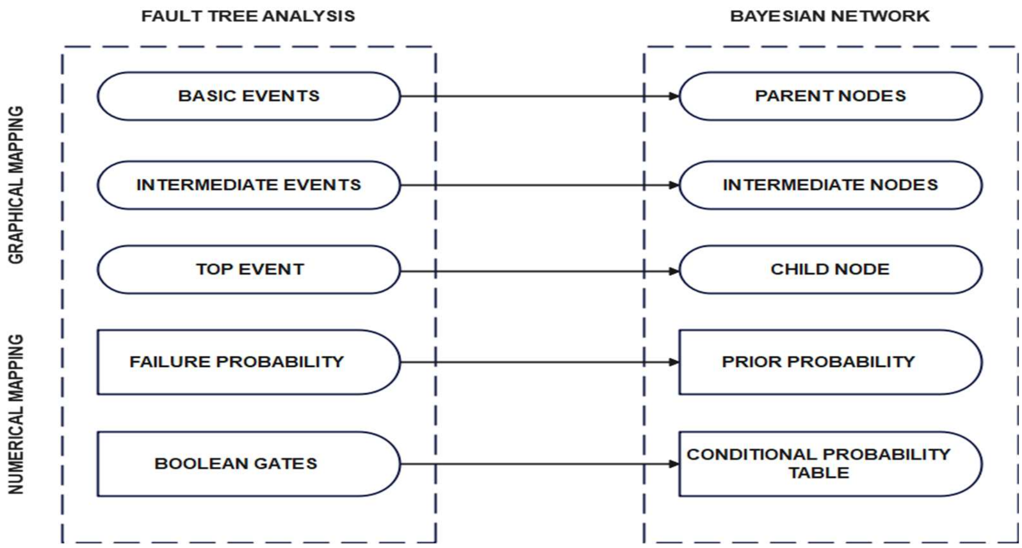

Fig. 8.6 Mapping of FT into BN

The conditional probability table (CPT) provides a logical relationship among the nodes. A summarized description of the mapping process has been mentioned by Bobbio et al. (2001) in their work. Some additional information regarding the mapping process has been obtained from their work, which is mentioned below:

1. For each BE, one parent nodes have to be created. However, if more leaves of the FT represent the same BE, just one parent node has to be created.
2. For each gate mentioned in FT, a corresponding node has to be created in BN, provided equivalent CPT has to be added on that node.
3. Connection of nodes in BN corresponding to the connection of gates in FT.

To minimise the uncertainties between the parent node and child node, amended CPT can be added to nodes corresponding to gates using experts' opinions (Sakar et al. 2021). Based on the FT diagram as shown in Fig. 7.4, the BN has been portrayed in Fig. 8.7. After chalking out the BN, this work has headed towards the evaluation of the posterior probability of the BEs. The Bayesian interference approach has been adopted for such enumeration, as discussed in the theory part. Let P(A) be designated as the FP of any BE 01, which is the prior probability of the same, and P(B) be termed as the FP of the system. Then, according to Bayes' theorem, the probability that the cause of system failure is the BE 01 is given by:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} = \frac{P(B,A)}{\sum AP(B,A)} \tag{8.18}$$

P(A|B) is the posterior probability of BE 01. Likewise, the posterior probability of other BEs has been calculated in the same manner. Based on the values of the posterior probabilities, the sensitive BEs affecting the top event most have been identified and ranked in a descending manner.

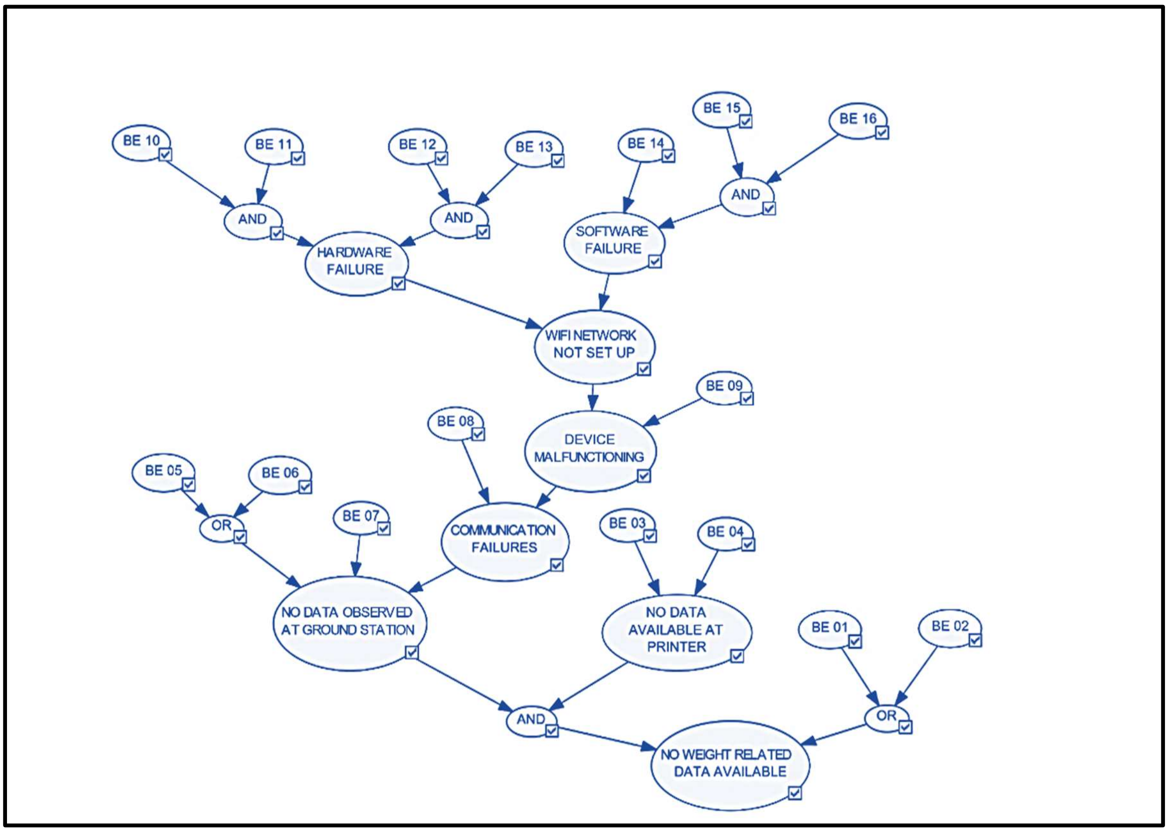

Fig. 8.7 BN of the Intelligent weight data communication system

8.2.5 Development of RUL prediction equation using ARIMA model

Auto-regressive Moving average (ARMA) is a forecasting model that can be identified based on a stationary time series (Jaggia, 2010). The stationary series implies no variation of mean and variance in the series. In case of a non-stationary data series, by differencing the adjacent periods, it has to be converted to a stationary data series known as the Auto-regressive Integrated Moving average (ARIMA) model. The stationarity of time series has been further divided into strict and weak stationarity (Lu et al. 2020). The time series chosen in the ARIMA model is weakly stationary, which indicates retention of the correlation coefficient of the time series. Based on the literature reviews, the mathematical representation of the ARIMA model can be represented as:

$$y_t = \mu + \sum_{i=1}^{p}(\emptyset_i y_{t-i}) + \epsilon_t + \sum_{j=1}^{q}(\theta_i \epsilon_{t-j}) \quad (8.19)$$

Where y_t is the current health condition of the basic events. Other terms like μ, ϕ_i, and θ_j are constant terms, Autocorrelation, and Partial Autocorrelation coefficient, respectively. ε_t is the error term at time t and is also known as white noise. On the other hand, p and q are the orders of the Auto Regression (AR) and Moving Average (MA) models, respectively. The detailed method of the ARIMA model has been elaborated by Makridakis et. al. (2008) and discussed all the necessary associated steps. The steps are given below:

A. Data Preparation
B. Model Selection
C. Estimation of parameters
D. Diagnostics of Residuals
E. Use the model to forecast

As already said, the stationarity of the series has to be achieved before adopting the ARIMA model. The differencing (d) of two consecutive values of the existing series has been evaluated to construct a stationary series as stated in equation 8.20. The Augmented Dicky Fuller test has been conducted for stationarity checking. This test has been carried out using Minitab software.

$$\delta_{y_t} = (y_t - y_{t-1}) \tag{8.20}$$

After the construction of the stationary series, the proper order of AR and MA models has to be evaluated because the ARIMA model is comprised of both of them. The said orders have been derived from the Partial Auto-correlation function (PACF) plot and Auto-correlation function (ACF) plot, respectively. The ACF and PACF values have been calculated using Equations 8.21 and 8.22, respectively.

$$r_k = \frac{\sum_{t=1}^{n-k}(y_t - y_{Mean})(y_{t+k} - y_{Mean})}{\sum_{t=1}^{T}(y_t - y_{Mean})^2} \tag{8.21}$$

Where n is the number of observations

$$\rho_{k,k} = \begin{cases} r_1 & if\ k = 1, \\ \dfrac{r_k - \sum_{j=1}^{k-1}(\rho_{k-1,j}.r_{k-j})}{1 - \sum_{j=1}^{k-1}(\rho_{k-1,j}.r_j)} & if\ k = 2,3,\ldots \end{cases} \tag{8.22}$$

After obtaining the values of p, d, and q, the full ARIMA (p, d, q) has been developed by estimating the parameters like μ, ϕ_i, θ_j, and ε_t. Based on the parameters, the RUL predicting equation has been generated. The method of least squares, along with Regression analysis, has been used for parameter estimation. Due to high complexity, the entire estimation has been carried out using Minitab software. Based on the output, Equation 8.19 has been rewritten by placing the parameter values at appropriate places. Hence, a complete RUL predicting equation has been generated and discussed in the next section, along with a detailed discussion of FFFTA and BN-based diagnosis.

8.3 Results and discussion

The FFFTA has been conducted based on the judgment of the experts provided in Table 8.7. The traditional results obtained from FFTA have also been included in the table for comparison and validation. The values of the BEs have been considered as the prior probability of the respective parent nodes of the BN during the mapping process. The mapping process and calculation of posterior probabilities of BEs have been evaluated on GeNIe 4.1 software, as it is very complex. According to the values of posterior probability, the severity of BEs is considered in descending order and ranked according to it, as shown in Table 8.8.

BEs	Failure Probability results based on FFTA (Hour-wise)				Failure Probability results based on FFFTA (Hour-wise)			
	2500	**5000**	**7500**	**10000**	**2500**	**5000**	**7500**	**10000**
F01	0.007083	0.020589	0.040497	0.06056	0.006783	0.019688	0.038767	0.058397
F02	0.014996	0.030979	0.044841	0.063431	0.015075	0.029776	0.043482	0.066287
F03	0.005	0.014996	0.029984	0.044841	0.005	0.015075	0.028855	0.043482
F04	0.002013	0.005	0.007439	0.014996	0.001866	0.005	0.007623	0.015075
F05	0.005	0.014996	0.030979	0.063431	0.005	0.015075	0.029776	0.066287
F06	0.010371	0.020589	0.06056	0.153213	0.010183	0.019688	0.058397	0.195779
F07	0.003254	0.010371	0.029984	0.044841	0.003148	0.010183	0.028855	0.043482
F08	7.4E-06	3.8E-05	0.000118	0.000704	5.18E-06	3.16E-05	0.000129	0.000673
F09	0.000118	0.00031	0.001251	0.005	0.000129	0.000337	0.00122	0.005
F10	8.91E-06	0.000118	0.000704	0.001325	6.56E-06	0.000129	0.000673	0.002179
F11	0.000725	0.001251	0.002056	0.003445	0.000776	0.00122	0.002087	0.003607
F12	0.000118	0.001251	0.005	0.0072	0.000129	0.00122	0.005	0.007378
F13	0.000664	0.002013	0.003254	0.005	0.000636	0.001866	0.003148	0.005
F14	0.000298	0.001251	0.002146	0.00338	0.000279	0.00122	0.002179	0.005
F15	3.17E-07	6.72E-06	3.8E-05	0.000118	2.33E-08	2.58E-06	3.16E-05	0.000129
F16	3.17E-07	3.17E-07	7.4E-06	7.4E-06	2.33E-08	2.33E-08	5.18E-06	5.18E-06
Overall System	0.022102	0.051816	0.087617	0.133132	0.02188	0.04975	0.084428	0.135547

Table 8.7 Event-wise Failure Probability

Though both FFTA and FFFTA displayed very close results, the experts have considered FFFTA over FFTA as it provides more precise failure probabilities of the BEs. Apart from that, a significant difference can be observed between the two methods during the evaluation of overall system failure probability, and the result of the FFFTA has been found superior as compared to FFTA based on the expert's elicitation. The practising plant Engineers, other than the experts, involved with the said systems, have echoed the same observations. Thus, it validates the results. The proposed methodology is easy to understand, easy to use and easy to compute the results. Additionally, the FFS considers both the degree of membership as well as the degree of non-membership while dealing with uncertainty and incomplete data. It explores and exploits the hidden components present in the system. Thus, it outlines the distinct advantages over the traditional one. Considering the following factors, the FFFTA has been chosen for the case study. Period-wise Pareto analysis has been conducted and displayed below.

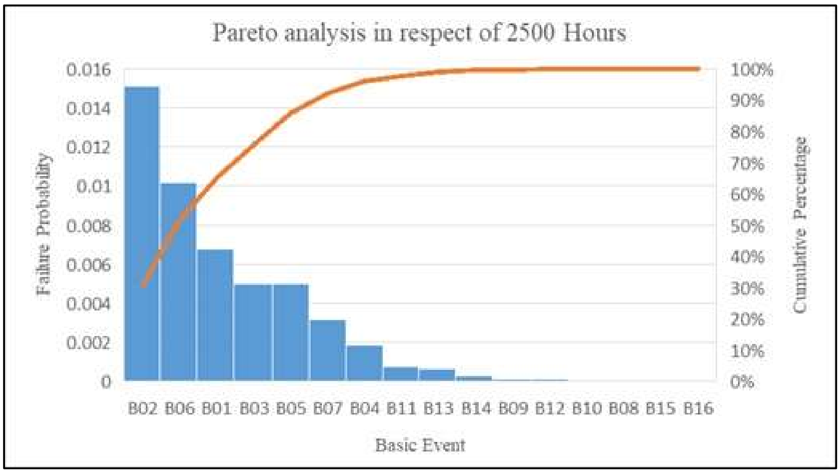

Fig. 8.8 Pareto Analysis of the System for 2500 Hours of Operation

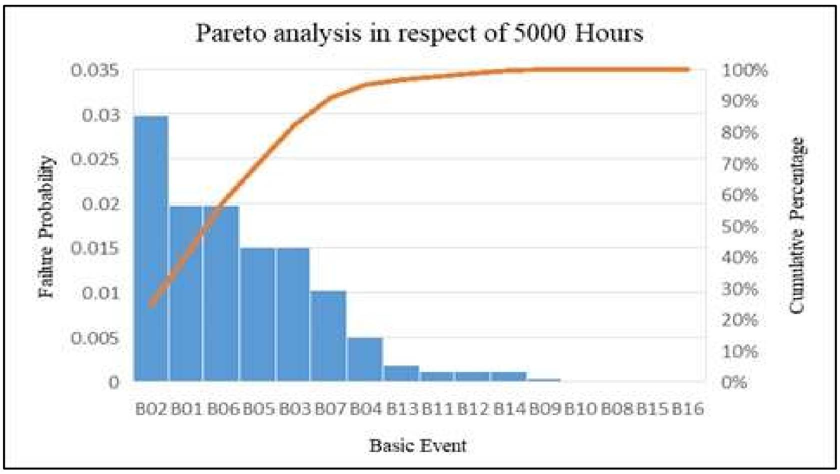

Fig. 8.9 Pareto Analysis of the System for 5000 Hours of Operation

P.T.O

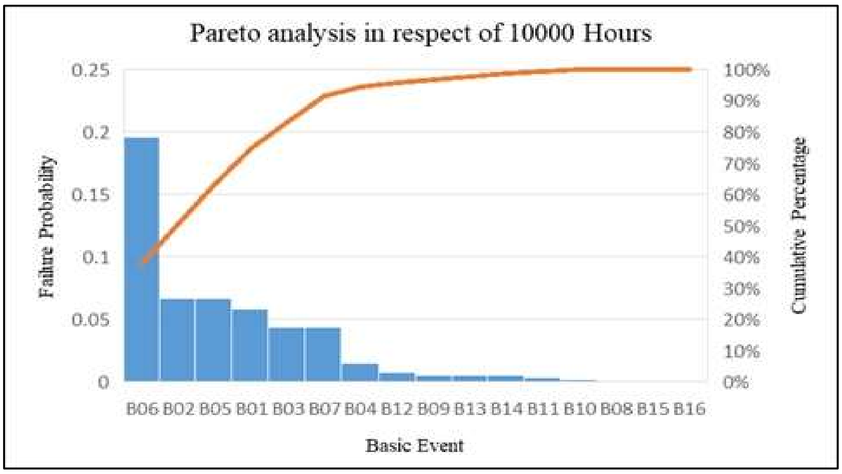

Fig. 8.10 Pareto Analysis of the System for 7500 Hours of Operation

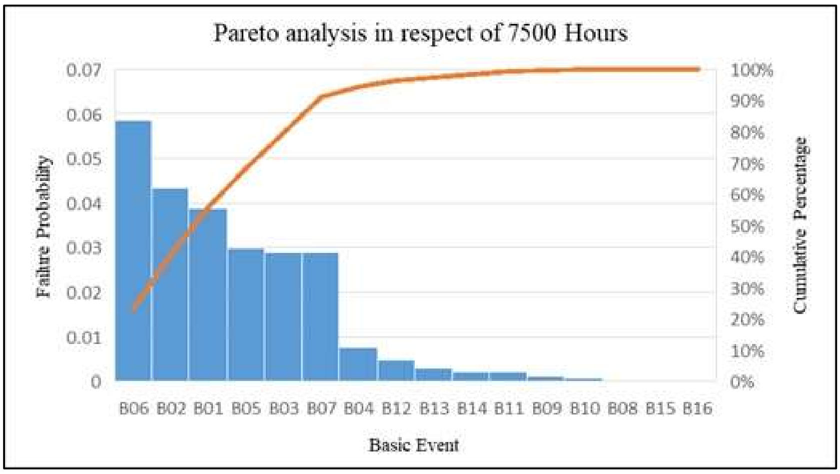

Fig. 8.11 Pareto Analysis of the System for 10000 Hours of Operation

It is evident from figures 8.8 to 8.11 that 20% of BEs are responsible for 80% of the problems. Hence, it corroborates the Pareto principle. The five major basic events, as found from the Pareto chart, need very careful attention during the operational state of the system. The implication of the proposed study reveals:

A. Types of maintenance strategy to be taken.
B. Inventory control of the spare parts.
C. Budgetary planning for procurement of spare parts.
D. Available skill manpower and other accessories for the said purpose.

Based on the results and experts' opinions, the Top five ranked events, i.e., BE 02, BE 01, BE 06, BE 03, and BE 05, have been considered critical events, and prognostic assessment for RUL prediction has been suggested. Among the five BEs, the top priority has been given to BE 02, i.e. Weight processor failure, because both the PP and S values are higher for the said event throughout the observation. This is because of the excessive use of the crane for material handling.

BEs	**Posterior Probability (PP) and Sensitivity (S) of the BEs for different periods in Hours**							
	2500		**5000**		**7500**		**10000**	
	PP	**S**	**PP**	**S**	**PP**	**S**	**PP**	**S**
F01	0.309984	0.985	0.395747	0.969	0.459165	0.952	0.430827	0.918
F02	0.688975	0.993	0.598518	0.979	0.515022	0.957	0.489036	0.926
F03	0.009139	0.018	0.028016	0.043	0.063965	0.106	0.120382	0.251
F04	0.00341	0.018	0.009293	0.043	0.0169	0.104	0.041736	0.243
F05	0.006505	0.007	0.020575	0.018	0.040171	0.03	0.083977	0.039
F06	0.013246	0.007	0.026872	0.019	0.078782	0.031	0.248027	0.045
F07	0.004095	0.007	0.013898	0.018	0.038927	0.03	0.055087	0.038
F08	6.73E-06	0.007	4.31E-05	0.018	0.000174	0.029	0.000853	0.036
F09	0.000168	0.007	0.00046	0.018	0.001646	0.03	0.006335	0.036
F10	6.56E-06	0	0.000129	0	0.000674	0	0.002181	0
F11	0.000776	0	0.00122	0	0.002087	0	0.003609	0
F12	0.000129	0	0.001221	0	0.005006	0	0.007387	0
F13	0.000636	0	0.001866	0	0.003154	0	0.00501	0
F14	0.000363	0.007	0.001665	0.018	0.002939	0.03	0.006335	0.036
F15	2.33E-08	0	2.58E-06	0	3.16E-05	0	0.000129	0
F16	2.33E-08	0	2.33E-08	0	5.18E-06	0	5.18E-06	0

Table 8.8 Results obtained from BN

The FFFTA has provided only four data points for four periodical observations. For prognostic operation, more data are needed. To overcome the barriers, period-wise intermediate random degradation data has been generated in ascending order, which has also been verified by the experts and plotted against their respective time in Fig. 8.12. The Augmented Dicky-fuller tests have been carried out for stationarity check of the time series, and the result has been portrayed in Table 8.9. To satisfy stationarity, the Test value should be less than the critical value.

P.T.O

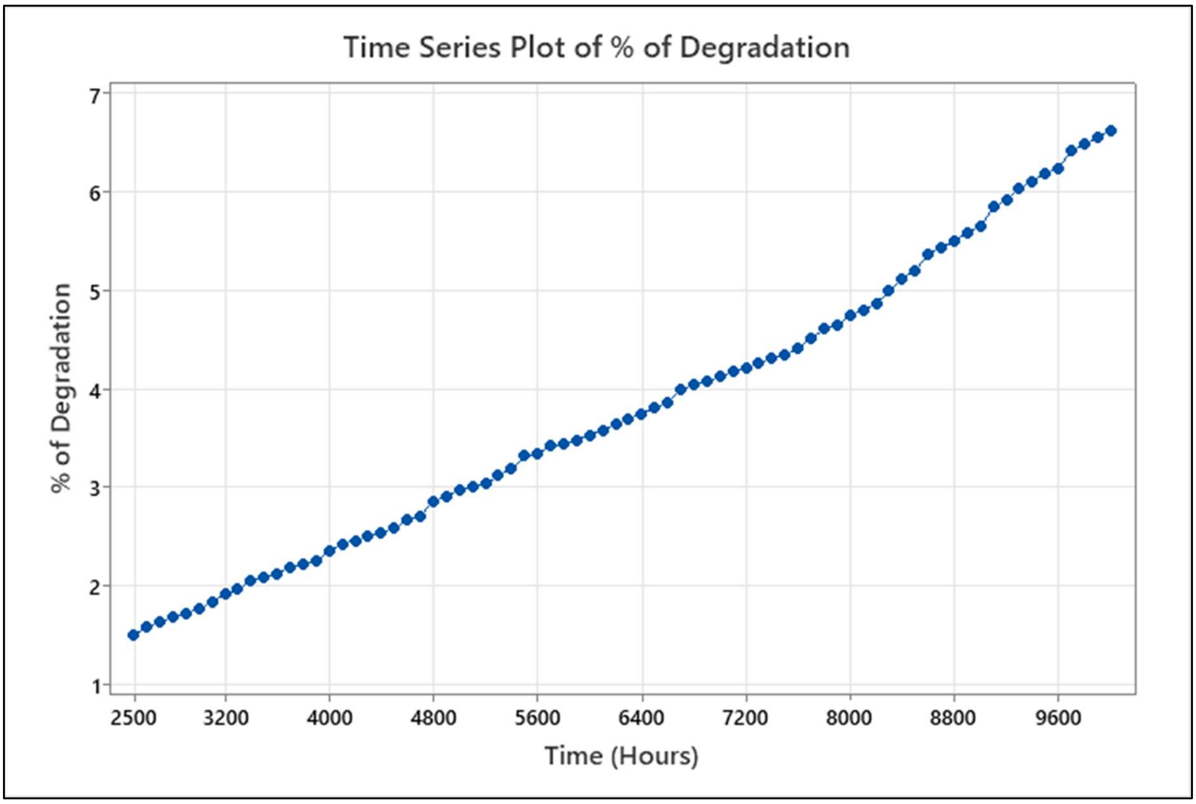

Fig. 8.12 Periodical Degradation of BE 02

Test Statistic	P-Value	Recommendation	Remarks
3.32354	1.000	Test statistic > critical value of -2.90092	Consider differencing to make the data stationary

Table 8.9 Augmented Dicky-Fuller Test result for the time series

As the stationarity has not been achieved, the first differencing of degradation data has been calculated, and the corresponding Augmented Dicky-fuller test has been performed for stationarity check and exhibited in Table 8.10. The result has suggested further differentiation.

Test Statistic	P-Value	Recommendation	Remarks
-1.32488	0.618	Test statistic > critical value of -2.90509	Consider differencing to make the data stationary

Table 8.10 Augmented Dicky-Fuller Test with respect to first differentiation

Considering the results of the first differentiation, the second one has been performed as stationarity has not been achieved, and the respective dataset against the time is shown in Fig. 8.13. The results of the Augmented Dicky-fuller test are displayed in Table 8.11.

Test Statistic	P-Value	Recommendation	Remarks
-7.12360	0.000	Test statistic ≤ critical value of -2.90509	Data appears to be stationary, not supporting differencing.

Table 8.11 Augmented Dicky-Fuller Test with respect to second differentiation

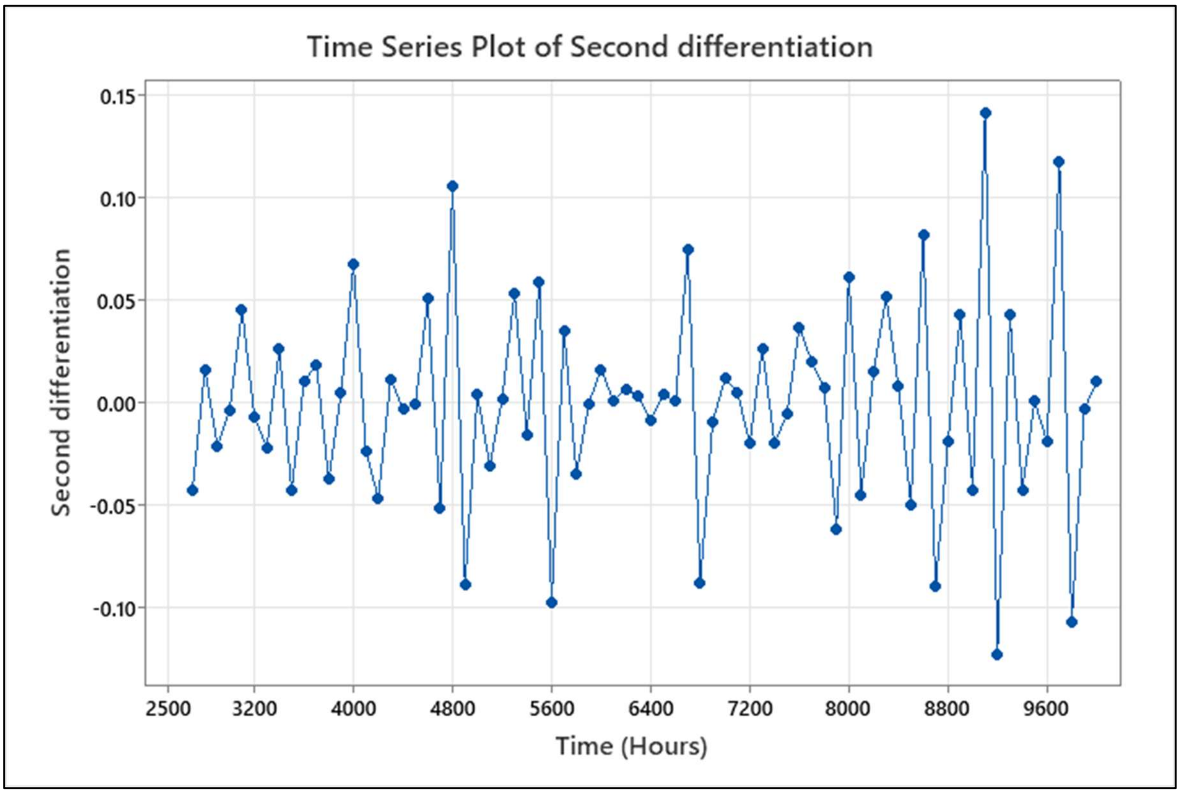

Fig. 8.13 Second differentiation of Periodical Degradation data for BE 02

Based on the conclusion of Table 8.11, the PACF and ACF have been plotted using second differentiation data to retrieve the order of AR (p) and MA (q), as shown in Fig. 8.14 and Fig. 8.15, respectively. As per the knowledge gathered from the literature survey, the expert's knowledge, and the nature of the spikes of both plots, the values of p and q have been considered as 1 and 1, respectively. Hence, the ARIMA (1,2,1) time series model has been implemented to generate the RUL prediction equation of BE 02. Based on the above model, the values of μ, ϕ_i, and θ_j have been enumerated for the construction of the RUL prediction equation as shown in Table 8.12.

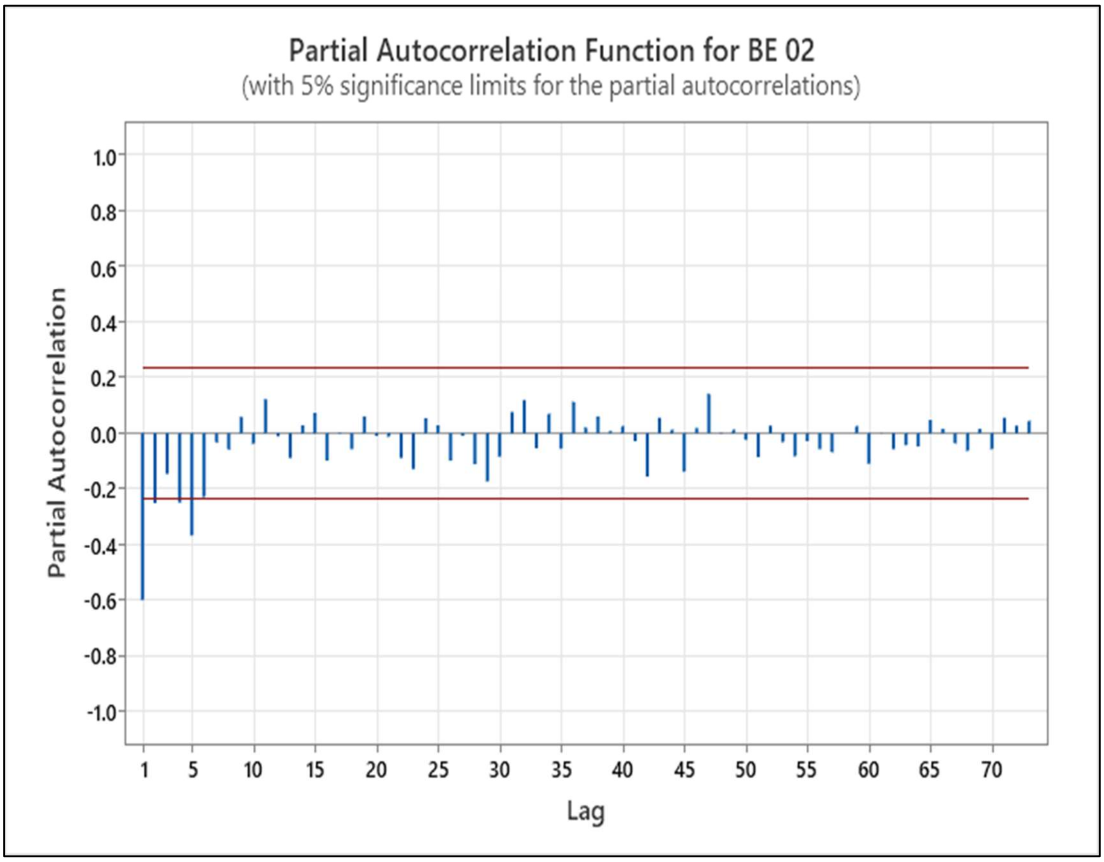

Fig. 8.14 PACF plotting of second Differencing of Degradation Data of BE 02

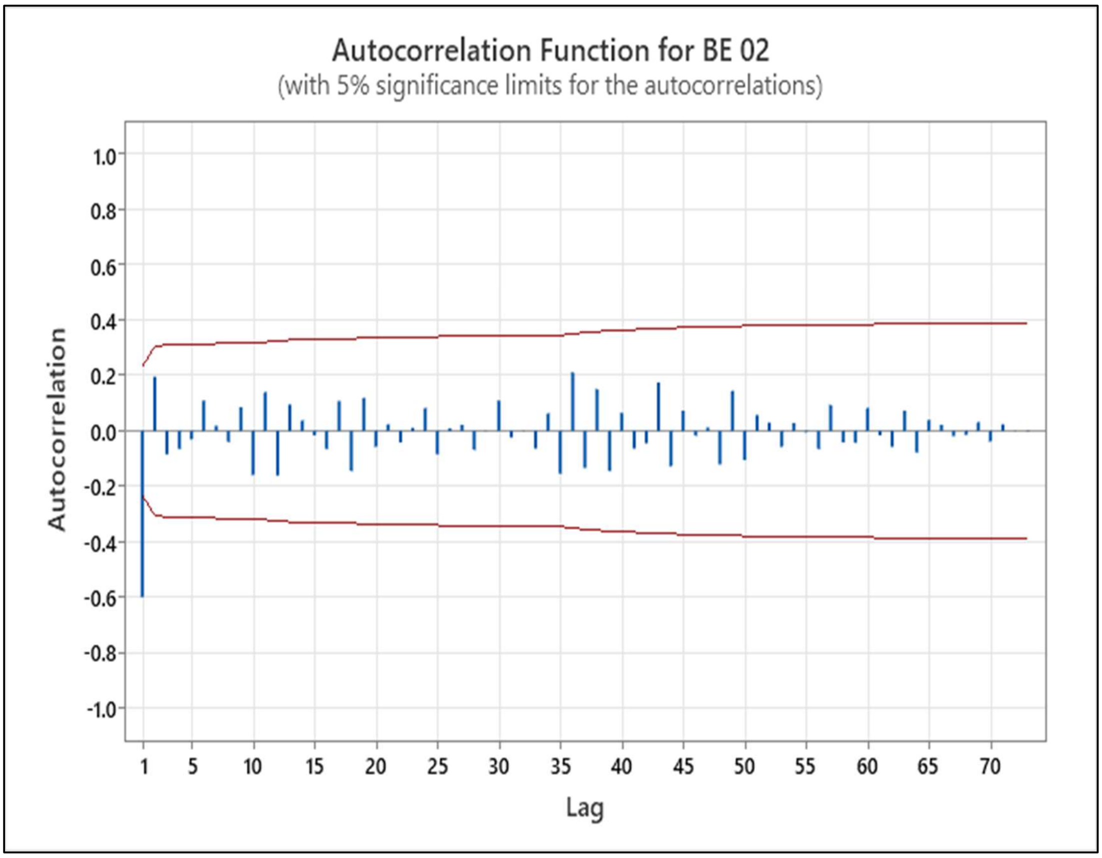

Fig. 8.15 ACF plotting of second Differencing of Degradation Data of BE 02

Type	Co-efficient	Standard Error of Coefficient	T-Value	P-Value
AR 1	-0.103	0.121	-0.85	0.400
MA 1	0.9699	0.0474	20.45	0.000
Constant	0.000643	0.000185	3.48	0.001

Table 8.12 Detailed Result of ARIMA (1,2,1) Model for BE 02

The requisite data, which are presented in Table 8.12 used to construct the RUL predicting equation of the BE 02. The data have been inserted in equation 8.19 and rewritten as:

$$y_t = 0.000643 - 0.103(y_{t-1}) + \varepsilon_t + 0.9699(\varepsilon_{t-1}) \quad (7.23)$$

The residual sum of the squares of the series has been calculated as 0.0803849, through which the variance of the ε_t can be estimated. Therefore, the Mean square error (MSE) can also be estimated from the said variance. Readers are encouraged to review the ARIMA model's literature surveys for further details.

Chapter 9

Conclusion

9.1 Conclusion of the Research Work

The research work "STUDY OF RELIABILITY, AVAILABILITY AND MAINTAINABILITY OF INDUSTRY 4.0 IN INDIAN PERSPECTIVE" has been carried out with the aid of 4 (four) numbers of case studies. The prime motto of the work has been identified through the gap analysis, which irradiates the aims and the objectives of the research work. Due to inadequate scopes, only 3 (three) domains have been identified as discussed earlier. The objectives of the work have been fulfilled through the domains with the help of expert elicitation.

The Entropy-Based Markov model has been applied for the Availability and Reliability assessment of a Smart factory system. Fuzzy set theory has an in-depth contribution to failure data assessment. It is evidence that, in spite of insufficient failure data, the problem has been addressed with the help of experts' experiences. Though the obtained result might have a marginal variation from the actual result, it has been considered for the case study as it does not require adequate precision. Moreover, it is useful to identify the trend of the failure data. Using the Entropy-Based Markov model, the consensus values of Availability and Reliability have been obtained after several iterations. Consensus values are the layer-wise optimum values of Availability and Reliability, which are responsible for obtaining the maximum values of system availability and reliability. This method could be considered for Reliability, Availability, as well as Maintainability assessment of other fields related to the Industry 4.0 domain under uncertain environments, and thus it justified the first objective of the research.

FMEA has unlocked the second objective of the research work, where the probable failures and their effects have been assessed. A smart Arsenic-Iron removal plant (AIRP) has been chosen as the case study. An in-depth concept of the Raugh set has been recapitulated in this section. Based on the thorough system studies, 8 (Eight) numbers of faults have been identified, which are responsible for either system failure or process malfunction. 5 (Five) numbers of criteria have been considered for the identification of failure based on their severity and ranked accordingly. A Rough set-based MCDM method named Rough-RIM (Rough-based Reference ideal method) has been applied for FMEA assessment as well as ranking of the failures. A comparative analysis among the results obtained from different techniques, e.g. R-RIM, R-TOPSIS, R-MABAC, have been utilized in this regard. The result shows the F06, i.e. Malfunction of automatic plunger type chlorinator, shows a significantly dominating behaviour in the overall ranking while evaluating through R-RIM as well as other methods as mentioned above. This is because of direct health hazards in the absence of adequate chlorination in the drinking water. On the other hand, the F05, i.e. Improper backwash operation, has also been proven as superior in ranking compared to other failures as measured by R-TOPSIS and R-MABAC method. But the result obtained by R-RIM has been declared as more authentic by the experts, and the same decision has been echoed by the rest of the operating members attached to the system. The sensitivity analysis has also reflected the F06 as the most stable failure with respect to different times and parameters, as compared to the other failures.

Subsequently, the application of an IoT-based weight data communication system, which is an instrument that falls under the Industry 4.0 domain, and its maintenance policy have also been discussed. This system has been adopted from an aluminium smelting plant, as stated before, but can also be used in different manufacturing sectors depending on its necessity. Under these circumstances, this system needs to be reliable as well as available; otherwise, a huge loss of resources might be faced by the concerned firm. To identify the faults of the system under an uncertain environment, FFTA has been used as a key tool, and its significance has been reflected in this work. Despite of unavailable failure data of the IOT system, it has successfully disclosed the probability of component-level failures. Based on detected failures, RCM has been adopted for unwanted hampers in production work as well as for the prevention of losses regarding work-related data. The RCM methodology used in the research work emphasizes replacement strategies based on the hazard rate (λ_S) of the components. A significant improvement in system reliability (R_S) has been observed after the completion of maintenance work, which implies betterment of system availability and sustainability, as well as denotes the third objective of the research work. The actual experimental result might slightly vary, as fuzzy set theory portrays the results based on expert elicitation, which has been found as the prime limitation of the study. On the other hand, only TFN has been considered for FFTA, though various studies have also considered TZFN (Trapezoidal Fuzzy Number) in this regard. Under these circumstances, a comparative analysis has to be considered for the betterment of the research work.

Addition of superior concept of fuzzy sets i.e. Intuitionistic fuzzy sets (Atanassov, 1986), Hesitant fuzzy sets (Torra, 2010), Fermatean Fuzzy Sets (Senapati et al., 2020), Neutrosophic fuzzy sets (Smarandache, 2010), Pythagorean fuzzy set (Yagar, 2013), etc. have not been addressed in the section, though, for a better outcome, and that concept has been addressed in the later part. Additionally, the concept of fault diagnosis and failure prognosis has been incorporated for the health assessment of the system. The fault diagnosis operation of the system using BN-based FFFTA analysis has been conducted in the study with a similar domain as discussed earlier. The FFS is the pillar of FFFTA and the upgradation of IFS. The outcome of the result was harmonized due to the utilization of both Membership and Non-membership functions. The FFFTA reveals the true reflection of the degradation percentage. The ARIMA model-based RUL estimation has been carried out thereafter in the study. Both Diagnostic and Prognostic approaches have been elaborated separately. From FFFTA analysis, it has been found that BE 06, i.e. 12-volt battery failure, is most vulnerable at the end of 10000 Hours of operation. This is because of battery has a limited life. While mapping into BN, it was found that BE 02, i.e. Weight processor failure, has the highest Posterior Probability value, which indicates as most influential BE for the entire system failure. The prime insight of the work is to improve the productivity of the IoT system and operate the process error-free. Based on the study, the responsible critical BEs have been identified for system failure through Pareto analysis and on the other hand, RUL predicting equation of the BEs have been generated through which the present condition of the system can be assumed. During the study, some limitations have also been observed, including Insufficient data generation, Estimation of residual terms in the ARIMA model, etc. Further study is required to overcome such limitations. However, the case study has provided a broader aspect of the diagnosis and prognosis of an engineering system that has been covered under an uncertain environment and at the same time fulfils the fourth objective of the study.

9.2 Future scope of the study

The above objectives of the research work emphasise on safe and sustainable operation of the system. Hence, a blueprint has been constructed to operate an Industry 4.0 domain by satisfying those objectives and enabling safe operation, as well as to secure the system safety. The said case studies have been adopted from Indian industries and thus justified the term "Indian Perspective". The overall study will contribute to the holistic growth of the Indian Industry, and an additional focus has been given to the emerging Industries related to Industry 4.0 domains. The study could be helpful form Indian viewpoint and it will be beneficial to incorporate the framework on the different sectors associated to Indian industries. The Artificial Intelligence (AI), Machine learning (ML), and other data driven approach might improve the robustness of the framework in future.

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